2008-09

Improved methodology for developing cost uncertainty models for naval vessels

Brown, Cinda L.

Monterey, California. Naval Postgraduate School

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

IMPROVED METHODOLOGY FOR DEVELOPING COST UNCERTAINTY MODELS FOR NAVAL VESSELS

by

Cinda L. Brown

September 2008

Thesis Advisor:	Edouard Kujawski
Second Reader:	Diana Angelis

Approved for public release; distribution is unlimited

THIS PAGE INTENTIONALLY LEFT BLANK

REPORT DOCUMENTATION PAGE				*Form Approved OMB No. 0704-0188*
Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188) Washington DC 20503.				
1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** September 2008		**3. REPORT TYPE AND DATES COVERED** Master's Thesis	
4. TITLE AND SUBTITLE Improved Methodology for Developing Cost Uncertainty Models for Naval Vessels			**5. FUNDING NUMBERS**	
6. AUTHOR(S) Cinda L. Brown				
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943-5000			**8. PERFORMING ORGANIZATION REPORT NUMBER**	
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) None			**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**	
11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.				
12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited			**12b. DISTRIBUTION CODE** A	
13. ABSTRACT (maximum 200 words)				

The purpose of this thesis is to analyze the probabilistic cost model currently in use by NAVSEA 05C to predict cost uncertainty in naval vessel construction and to develop a method that better predicts the ultimate cost risk. The data used to develop the improved approach is collected from analysis of the CG(X) class ship by NAVSEA 05C. The NAVSEA 05C cost risk factors are reviewed and analyzed to determine if different factors are better cost predictors. The impact of data elicitation, the Money Allocated Is Money Spent (MAIMS) principle, and correlation effects are incorporated into the research and analysis of this thesis. Data quality is directly affected by data elicitation methods and influences the choice of probability distribution used to give the best predictor of cost risk. MAIMS and correlation effects are shown to make a significant impact to the overall cost model. Program managers and analysts can readily implement the enhanced models using commercial Excel add-ins, such as Crystal Ball or @Risk, and integrate them into their current cost risk analysis and management practices to better mitigate risk and control project cost.

14. SUBJECT TERMS Cost Uncertainty, Cost model, Surface Ship, Estimation, Naval Vessel			**15. NUMBER OF PAGES** 85
			16. PRICE CODE
17. SECURITY CLASSIFICATION OF REPORT Unclassified	**18. SECURITY CLASSIFICATION OF THIS PAGE** Unclassified	**19. SECURITY CLASSIFICATION OF ABSTRACT** Unclassified	**20. LIMITATION OF ABSTRACT** UU

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. 239-18

THIS PAGE INTENTIONALLY LEFT BLANK

Approved for public release; distribution is unlimited

IMPROVED METHODOLOGY FOR DEVELOPING COST UNCERTAINTY MODELS FOR NAVAL VESSELS

Cinda L. Brown
Lieutenant Commander, United States Navy
B.S., United States Naval Academy, 1998

Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN SYSTEMS ENGINEERING

from the

NAVAL POSTGRADUATE SCHOOL
September 2008

Author: Cinda L. Brown

Approved by: Edouard Kujawski, Ph.D.
Thesis Advisor

Diana Angelis, Ph.D.
Second Reader

David Olwell, Ph.D.
Chairman, Department of Systems Engineering

THIS PAGE INTENTIONALLY LEFT BLANK

ABSTRACT

The purpose of this thesis is to analyze the probabilistic cost model currently in use by NAVSEA 05C to predict cost uncertainty in naval vessel construction and to develop a method that better predicts the ultimate cost risk. The data used to develop the improved approach is collected from analysis of the CG(X) class ship by NAVSEA 05C. The NAVSEA 05C cost risk factors are reviewed and analyzed to determine if different factors are better cost predictors. The impact of data elicitation, the Money Allocated Is Money Spent (MAIMS) principle, and correlation effects are incorporated into the research and analysis of this thesis. Data quality is directly affected by data elicitation methods and influences the choice of probability distribution used to give the best predictor of cost risk. MAIMS and correlation effects are shown to make a significant impact to the overall cost model. Program managers and analysts can readily implement the enhanced models using commercial Excel add-ins, such as Crystal Ball or @Risk, and integrate them into their current cost risk analysis and management practices to better mitigate risk and control project cost.

THIS PAGE INTENTIONALLY LEFT BLANK

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF SYMBOLS, ACRONYMS, AND/OR ABBREVIATIONS

CBO	Congressional Budget Office
CER	Cost Estimation Relationship
CG(X)	Cruiser
CNO	Chief of Naval Operations
CPI	Cost Performance Index
CRA	Cost Risk Analysis
DFA	Direct Fractile Assessment
EAC	Estimate at completion
EO-IR	Electro Optical-Infrared
EW-IW	Electronic Warfare-Information Warfare
ExComm	External Communications
FY	Fiscal Year
G & A	General and Administrative
GAO	United States Government Accountability Office
IFF	Information, Friend or Foe
IUSW	Integrated Undersea Warfare
LCS	Littoral Combat Ship
MAIMS	Money Allocated is Money Spent
MS EI&T (CS Only)	Mission Systems Engineering, Integration, and Testing (Combat Systems Only)
MS EI&T (SS Only)	Mission Systems Engineering, Integration, and Testing (Ship Systems Only)
NAVSEA 05C	Naval Sea Systems Command, Cost Engineering and Industrial Analysis Division
NSWC	Naval Surface Warfare Center
NRE	Nonrecurring Engineering Costs
PDF	Probability Distribution Function
PPBES	Planning, Programming, Budgeting, and Execution System
RV	Random Variable
SME	Subject Matter Expert
SPI	Schedule Performance Index
TOA	Total Obligation Authority
TRL	Technology Readiness Level
TSCE	Total Ship Computing Environment
VLS	Vertical Launch System
WBS	Work Breakdown Structure
X1	CG(X) First ship of class

THIS PAGE INTENTIONALLY LEFT BLANK

EXECUTIVE SUMMARY

In order to generate the funds to implement the 30-year plan of future ships and capabilities, the Navy must explore different options for cost savings. Fundamental to the success of complex projects, such as naval vessel construction, is the ability to control, manage, and communicate the status of the risk reduction effort throughout the development and production cycles (Kujawski & Angelis, 2007). It is recognized that the Navy and the shipbuilding industry need to change their technical and business shipbuilding strategies in order to achieve the goal of a future Fleet that balances both capability and affordability. Cost risk assessment and analysis is one tool that can be utilized to help recapitalize costs used in the ship acquisition and building process.

This thesis analyzes the probabilistic cost model currently in use by Naval Sea Systems Command Cost Engineering and Industrial Analysis Division (NAVSEA 05C) to predict cost uncertainty in naval vessel construction and to develop a method that better predicts the ultimate cost risk. The NAVSEA 05C's cost analysis model for the proposed new cruiser, CG(X), encompasses all aspects of cost for the entire Fleet, including inflation and profit. The data used in the NAVSEA model were acquired from subject matter expert (SME) inquiry using three-point estimates of high, most likely, and low values. The Navy is placing great emphasis on producing the best product for each dollar spent. In order to ensure the continued acquisition of CG(X), it is important that realistic cost risk analysis be performed so that program managers can make informed decisions.

The cost model elements investigated in this thesis include data elicitation methods, probability distribution function (PDF) choice, correlation effects, and Money Allocated is Money Spent (MAIMS) principle effects. The most significant impact is seen with MAIMS and data elicitation effects. PDF choice and correlation effects have lesser impact upon the cost model.

Methods of data elicitation are explored and the use of a direct fractile assessment (DFA) is recommended for future use (Kujawski, Alvaro, and Edwards, 2004), although the research in this thesis did not involve data acquisition. To simulate the use of a DFA

methodology, three-parameter Weibull distributions are employed to account for uncertainty associated with SME estimation of data. A Weibull (10%, 50%, 90%) distribution is used to simulate a more optimistic view of the uncertainty of data, while a Weibull (20%, 50%, 80%) distribution models a more pessimistic view.

The methodology in choosing different probability distribution functions and their applicability to the model is evaluated. Specifically, triangular, lognormal, and two variations of the three-parameter Weibull distribution are considered. Once enhanced models are established, program managers can implement them into their current cost risk analysis practice to mitigate risk and control project cost.

Two types of correlation effects are considered and modeled in this thesis. The first is the correlation between the components of the radar suite, and the second is the correlation between all the components of the electronics suite. The radar suite is one of the systems that make up the electronics suite. The results suggest that the correlation effects are important for probability values midway between the mean and the extremes, but there is little difference for correlation coefficients beyond 0.5. Further investigations are recommended to quantify correlation effects.

MAIMS modified probability distributions are used to show the significance of budget allocation levels (Kujawski, Alvaro & Edwards, 2004). These distributions reflect an empirically observed effect, namely, that once a budget is allocated, the project cost will most likely be at least equal to the amount allocated. As the MAIMS modification value increases, the overall distribution cost rises with increasing probability.

Credibility and realism are two key cost risk assessment criteria. The use of improved methods, such as those investigated in this thesis, are especially significant for today's Navy during a time of budget hardship. If the Navy's plans for a 313-ship Fleet are to become a reality, the incorporation of cost risk analysis into acquisition and shipbuilding management is imperative. Reliable cost assessments can help deliver projects on time, at a lower cost, with a higher probability of success. Effective training of personnel involved in cost assessment and continued efforts to improve existing cost models will help to improve the Navy's current cost estimating process.

ACKNOWLEDGMENTS

I thank Dr. Edouard Kujawski for his time and mentoring throughout the research and writing of this thesis. I also thank Dr. Diana Angelis for her guidance and assistance in the development of this thesis. Additionally, I thank Mr. Chris Deegan, the former Director of Cost Engineering and Industrial Analysis, and his staff for providing the data used in this thesis; supporting travel to their office in Washington, D.C.; and discussions regarding the CG(X) model. Specifically, the help provided by Mr. Morris Fields and Mr. Aaron Ratliff with the CG(X) model is greatly appreciated.

I would also like to thank my special friends Lynne and Charlie Denley for making me a part of their family and their support during my time at the Naval Postgraduate School. In addition, I thank the members of the Wednesday Night Laundry Runners and my dogs for their friendship and good times.

THIS PAGE INTENTIONALLY LEFT BLANK

I. INTRODUCTION

Admiral Gary Roughead stated in the Chief of Naval Operation's (CNO) Guidance for 2007-2008 that:

> **We manage risk.** We will identify, analyze, mitigate and then accept risk, appreciating that we must always consider the risks in aggregate across the entire force. Zero risk is not achievable nor affordable. We must manage risk and move forward to accomplish the mission while safeguarding our people and infrastructure (Roughhead, 2007).

Vice Admiral K. M. McCoy took this a step further in 2008, in a statement made on assuming the position of Commander, Naval Sea Systems Command:

> Our Common mission is to develop, deliver and maintain ships and systems on time and on cost for the Navy. To build an affordable future fleet, we will focus on reducing acquisition costs, including applying more risk-based decisions to specifications and requirements . . . (McCoy, 2008).

The United States Navy is living and functioning in an era of ever expanding technology, more stringent requirements, and a growing need for more ships and resources, all while working with a limited budget. These factors all lead to inherent cost growth in the projects that are developed to provide the Fleet with the capabilities that it needs. In order for the United States Navy to acquire and provide a full, state-of-the-art, 313-ship Navy by 2020, as stated in the fiscal year (FY) 2007 plan (Department of the Navy, 2006, it is imperative that methods allowing full capitalization of each dollar spent by the Navy are developed and implemented.

In February 2006, the United States Navy presented its FY2007 plan, which outlines the objective of increasing the current 285-ship Fleet to 313 ships by 2020 (Department of the Navy, 2006). By 2008, the Navy increased the estimate of its annual cost for the 30-year plan by about 44% in real terms, but it is still approximately 7% less than independent cost estimates conducted by the Congressional Budget Office (O'Rourke, 2008). This increase in estimated cost poses a problem for the overall funding of the shipbuilding strategy proposed by the Secretary of the Navy. The

credibility of the Navy's estimates and the ability to fund its shipbuilding plans have been questioned by Congress and industry (Cavas, 2008b).

In order to adequately generate the funds to implement the 30-year plan of future ships and capabilities, the Navy must explore different options for cost savings. Fundamental to the success of complex projects, such as naval vessel construction, is the ability to control, manage, and communicate the status of the risk reduction effort throughout the development and production cycles (Kujawski & Angelis, 2007). It is recognized that the Navy and shipbuilding industry need to change their technical and business shipbuilding strategies in order to achieve the goal of a future Fleet that balances both capability and affordability. Cost risk assessment and analysis is one tool that can be utilized to help recapitalize costs used in the ship acquisition and building process.

A. BACKGROUND

Risk analysis is an important component of the cost analysis of new vessels because actual costs will always have a probability of differing from the estimate. Several reasons account for the difference between the estimate and actual cost, which can include lack of knowledge about the future, errors associated with assumptions and cost estimating equations, historical data inconsistencies, and factors considered in making the estimate. The overall purpose of risk analysis is to quantify the potential for error (Government Accountability Office (GAO), 2007). In the case of a cost estimate it is the probability that the actual cost will exceed the cost estimate or the budget. This cost estimate allows for the assessment of risk of a given program.

Cost overruns and growth are an enduring problem that is not new to the Navy. A 1939 inquiry from Secretary of the Navy Ray Spear asks the question, "Why do naval vessels cost so much?" In the answer to this inquiry, the reasons given include increased progress in marine engineering and naval construction, increased horsepower in shipbuilding, improved quality of building materials, inflation, and the practice of paying full price for the best you can buy naturally increases costs. Spear (1939) states that, "care must be taken in approving estimates to make sure that they are reasonable and held to in the cost of production. When contracts are negotiated the question of costs should be investigated and a detailed knowledge of approximate costs obtained." Just as it was

recognized by the Secretary of the Navy in 1939, it is recognized by today's Navy leadership that cost estimation is an integral part of the ship acquisition process.

The Defense Acquisition Acronyms and Terms (2003) defines risk as:

> A measure of the inability to achieve program objectives within defined cost and schedule constraints. Risk is associated with all aspects of the program, e.g., threat, technology, design processes, or Work Breakdown Structure (WBS) elements. It has two components, the probability of failing to achieve a particular outcome, and the consequences of failing to achieve that outcome.

Risk analysis and management can be used to help program managers more effectively make acquisition decisions and allocate their resources by allowing for a better understanding of program risks. Risk management is a continuous process in the acquisition and development of naval vessels.

The Naval Sea Systems Command, Cost Engineering and Industrial Analysis (NAVSEA 05C) introduced Cost Risk Analysis (CRA) into the Navy's PR09 Planning, Programming, Budgeting, and Execution System (PPBES) to help assess vessel costs in terms of quantifiable risk. Cost Risk Assessment is defined as the process of quantifying the uncertainties associated with major acquisition programs. It therefore allows for informed decisions with an estimated level of confidence (McCarthy, 2008).

Typical sources of cost uncertainty in naval vessel construction are (Deegan & Fields, 2007):

- <u>Estimating Methodology</u>. Cost Estimation Relationships (CER); learning/rate/curve assumptions; and cost-reduction initiatives.
- <u>Economic/business Factors</u>. Rates-wages, overhead, General and Administrative (G & A), etc.; Vendor/supplier stability; Inflation indices; Multiyear assumptions.
- <u>Technical Factors</u>. Technology Readiness Level (TRL); design and manufacturing complexity; software complexity; part or technology obsolescence.
- <u>Schedule Factors</u>. Potential for schedule delays, how schedule risks impact costs.

- <u>Program Specific Issues</u>. Requirements change, quantity change, funding uncertainty.
- <u>Errors of Omission and Commission</u>. Failure to account for rework.
- <u>Other Factors</u>. Strikes, acts of nature, accidents.

One of the key objectives of CRA is to enable better risk management, which will simultaneously reduce program costs and increase the probability of success. Cost estimating is recognized by NAVSEA 05C as an essential element of effective program management, required for realistic program planning and decision making. Risk analysis is important because the previous methodology of using point estimates is "precisely wrong" (Deegan, 2007a). Risk cannot be assessed with a point estimate, as it represents a single value that serves as a best guess for the parameter to be defined. Decision makers may not be able to completely understand the influence of different variables on cost with the use of a point estimate. Conversely, the use of risk analysis allows the decision maker to utilize their acquisition experience, while quantifying the qualitative aspects of acquisition scenarios.

Point estimates are not an accurate method for predicting costs in shipbuilding because they do not properly account for problems that may be encountered in the acquisition process, as described above. They may be either overly optimistic or overly pessimistic. Optimistic point estimates ignore the potential risk and uncertainty in a project, which is necessary for management to make informed decisions. Immature technology, uncertain product design, schedule problems, and unforeseen events all have risk associated with their end product. Risk analysis is necessary in order to incorporate the effect of risk into the overall cost. Pessimistic point estimates assume worst scenarios and unlikely high costs. Quantitative risk analysis allows the cost estimator to assign a realistic range of costs around a point estimate, which provides decision makers with a level of confidence in achieving a credible cost.

The *NAVSEA Cost Estimating Handbook* (2005, p. 3-1) states:

> Cost estimators must be proficient and aware of the financial management, performance measurement, schedule analysis, acquisition management, as well as the technical aspects of a program to support the cost estimating process effectively.

The NAVSEA Cost Estimating Process is comprised of three parts, which are further divided into 12 tasks. The three parts are: Develop Approach, Perform Estimate, and Brief Results. Figure 1 shows the breakdown of the 12 tasks within the three parts. This thesis focuses on the Develop Approach and Perform Estimate parts of the cost estimating process.

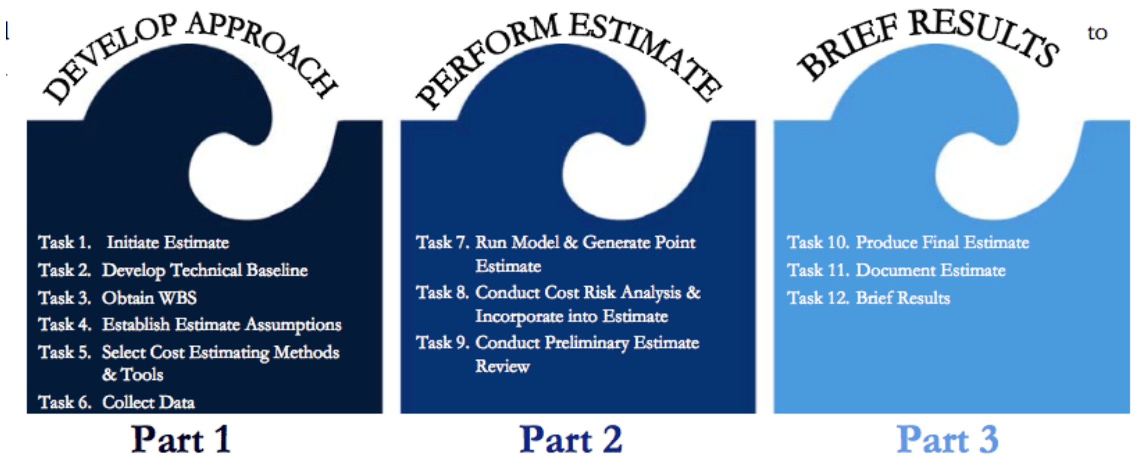


Figure 1. NAVSEA 12-Step Cost Estimating Process (From: NAVSEA Cost Estimating Handbook, 2005)

This thesis addresses the first two parts of the cost estimating process depicted in Figure 1—Develop Approach and Perform Estimate. Data collection is a task within the Develop Approach part of cost estimation and can be regarded as the most important part of risk analysis. Bad data will produce bad results, regardless of the subsequent analysis. Data elicitation is often done ad hoc; however, several reliable methods and sources are available for data collection. Data quality is critical to the success of the analysis and plays a significant part in the results generated for cost estimation. This thesis will discuss improved methods for data collection in order to obtain more reliable and standardized data from subject matter experts (SMEs).

Risk analysts use probability distributions rather than point estimates to represent the possible outcomes of an event. There is a significant difference between a point estimate and a distribution, in that the distribution provides the full range of values with their associated probabilities, while the point estimate presents a single value. This allows program management to make budget decisions, based on desired confidence

levels. Quality may differ, based on the method of collection. Two methods commonly used for data collection include database queries and interviews of SMEs or stakeholders (Deegan & Fields, 2007). This thesis analyzes the current NAVSEA 05C Cruiser (CG(X)) probabilistic cost model including data elicitation.

The direct fractile assessment (DFA) method provides one of the most reliable and least bias-prone procedures for eliciting uncertain quantities from SMEs (Kujawski et al., 2004). Data elicitation from SMEs is innately uncertain; three findings from psychological experiments conducted by Alpert and Raiffia (1982) are:

- A systematic bias toward overconfidence is common.
- Extreme value judgment is poor.
- Maximum and minimum values are vague terms. What do these terms really mean?

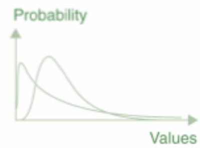
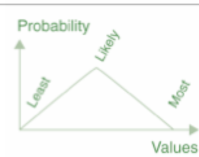
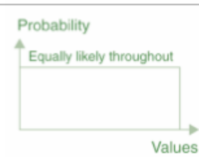
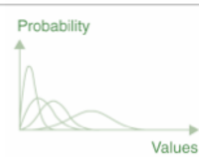
Based on the findings of Alpert and Raiffia (1982), Kujawski et al. (2004) propose the following guidelines for data elicitation:

- Ask SMEs to provide 10th, 50th, and 90th percentiles values for cost elements. Avoid extreme values, abstract measures such as the mean or standard deviation, or specific distribution functions. Allow for discussion and education of the SME in terms of bias when giving data figures.
- Calibrate each set of percentiles to reflect individual and project specific considerations, both pessimistic and optimistic. For estimates that might be overly optimistic, a cost analyst might choose to shift a 90th percentile value to perhaps 80th or 75th percentiles.

Tasks involved in the Performing Estimate depicted in Figure 1 are running the model and generating a point estimate or probability distribution, conducting a cost risk analysis, and conducting a preliminary estimate review.

Traditionally, triangular distributions have been used in cost estimation models because of the simplicity in entering the required data. The triangular distribution requires minimum or low, most likely, and high or maximum values. Other commonly

used distributions include normal, lognormal, and uniform. Table 1 lists eight of the most common probability distributions used for cost estimation and uncertainty analysis. This thesis investigates different methods for data elicitation and selecting appropriate distributions. The effects of using different distributions on cost risk are evaluated and identified.

Distribution	Description	Shape	Typical application
Lognormal	A continuous distribution positively skewed with a limitless upper bound and known lower bound; skewed to the right to reflect the tendency toward higher cost.		To characterize uncertainty in nonlinear cost estimating relationships.
Normal	Used for outcomes likely to occur on either side of the average value; symmetric and continuous, allowing for negative costs and durations. In a normal distribution, about 68% of the values fall within one standard deviation of the mean.		To assess uncertainty with cost estimating methods; the standard deviation or standard error of the estimate is used to determine dispersion.
Beta	Similar to normal distribution but does not allow for negative cost or duration, this continuous distribution can be symmetric or skewed.		To capture outcomes biased toward the tail ends of a range; often used with engineering data or analogy estimates.
Triangular	Characterized by three points—most likely, pessimistic, and optimistic values—can be skewed or symmetric and is easy to understand because it is intuitive. One drawback is the absoluteness of the end points.		To express technical uncertainty, because it works for any system architecture or design; also used to determine schedule uncertainty.
Uniform	Has no peaks because all values, including highest and lowest possible values, are equally likely.		With engineering data or analogy estimates.
Weibull	Versatile, able to take on the characteristics of other distributions, based on the value of the shape parameter "b"—e.g., Rayleigh and exponential distributions can be derived from it.[a]		In life data and reliability analysis because it can mimic other distributions and its objective relationship to reliability modeling.

Source: DOD, NASA, SCEA, and Industry.

[a]The Rayleigh and exponential distributions are a class of continuous probability distribution.

Table 1. Common Probability Distributions used in cost estimating uncertainty analysis (From: GAO Cost Assessment Guide, 2007)

The Money Allocated is Money Spent (MAIMS) principle is based on Parkinson's Law, where "Work expands to fill the time allotted" and "padding schedule estimates directly contribute to cost overruns" (Augustine, 1997). In other words, it

suggests that there will be no cost underruns, and that the project will come in at or above the cost to which it is funded. Implementing the MAIMS principle in Monte Carlo simulations modifies the basic probability distribution functions (PDF) by setting any value less than the money allocation point equal to that money allocation value. There will be no costs associated with a value less than this money allocation point. Utilizing the MAIMS principle, the PDFs are modified to include a spike or delta function at an arbitrary point, which is assumed to be the "money allocation point," corresponding to the dollar amount allocated to the program manager for the project and/or project cost elements.

Correlation effects between elements are analyzed. Correlation accounts for interrelationships between cost elements. Data elements can either be negatively, neutrally, or positively correlated and can either exist among cost elements within a subsystem or between elements in different subsystems. For example, take into consideration the elements of a ship. Positive correlation arise when increases in weight, size, and number of weapons systems onboard result in an increase in acquisition and shipbuilding costs. An increase in the complexity of a weapon system further forces an increase in cost of other systems such as power, cooling, control. Analysis would be greatly simplified if analysts could assume that all elements are independent, or that all elements are dependent. Since neither statement is true, correct correlation between elements is necessary to provide the most accurate representation of cost.

Many software programs are available for cost risk analysis. This thesis uses Crystal Ball® as an add-in to Microsoft Excel®, because of its ease of use and because it is the current program used by NAVSEA 05C. Crystal Ball® generates the Monte Carlo simulations that become the backbone of the cost risk analysis. A Monte Carlo simulation calculates multiple scenarios of a model by repetitively sampling values from the input variable distributions for each uncertain variable and then calculates the result. Depending on the complexity of the model, the analysis may take only a few moments or hours (Wittwer, 2004). The resulting cost distributions from Crystal Ball® provide the decision maker with powerful cost risk information.

A program built on a solid foundation of accurate cost estimating that effectively considers risks, combined with strong systems engineering and program management, gives the program a greater chance of success.

B. PURPOSE

The purpose of this thesis is to analyze the probabilistic cost analysis approach that NAVSEA's Cost Engineering and Industrial Analysis division (SEA 05C) currently uses to predict new naval vessel construction costs and to develop a method that better predicts the ultimate cost risk. This thesis uses data collected from analysis of the CG(X) class ship cost model. The model used to determine cost is reviewed and analyzed to determine what factors should be considered to produce more realistic cost estimates.

C. RESEARCH QUESTIONS

Several questions are addressed in this thesis. They include:

- What is the realism of the cost models currently in use by NAVSEA 05C for the CG(X) class ship?
- How does data elicitation impact the cost prediction?
- How does the choice of distributions in the model affect the predictions of the cost outcome?
- What is the impact of the MAIMS principle on the cost probability distributions?
- How can the current CG(X) model be improved to provide more accurate models to predict cost and risk?

D. BENEFITS OF STUDY

The benefit of this study is to provide an independent analysis of the cost model developed by NAVSEA 05C that is currently being used in their probabilistic cost analysis. This analysis will present alternatives that may be used to improve the current

approach, to more accurately predict the cost of a naval vessel and the risks associated with its development. The main focus is on data elicitation, choice of probability distributions, the MAIMS principle, and correlations. With the proposed cost analysis approach, the management involved in the development and construction of naval vessels will have a better tool to reduce program costs, while increasing the probability of success for each project.

E. SCOPE AND METHODOLOGY

Because of the complexity of the NAVSEA 05C CG(X) model, this thesis focuses on the analysis of the electronics portion. The electronics suite is comprised of nine different systems and related components. From this analysis, a model is developed to provide a more effective method to assess cost risk. Crystal Ball® software is used to provide analysis with the use of Monte Carlo simulations and charts to help quantify the importance of different risk factors and their link to the overall cost risk.

A literature review of risk assessment, project risk management, cost analysis, and cost modeling is conducted in Chapter II. Data is then analyzed in Chapter III, to determine how the NAVSEA CG(X) model was developed, what the assumptions were, what distributions were used, and if correlation effects were used. In Chapter IV, Crystal Ball® software is used to conduct Monte Carlo simulations on modified models to determine if there was any significant change in the cost based on proposed assumptions. In these simulations, experiments with different distributions, correlation effects, and truncation of the distributions to simulate the MAIMS principle are conducted. Finally, Chapter V summarizes the proposed cost risk analysis improvements that were investigated in this thesis.

II. LITERATURE REVIEW

A. INTRODUCTION

Cost estimation is a process that has been more closely scrutinized in recent history because of the increasing trouble with cost overruns by major programs. The Littoral Combat Ship (LCS) is an example of gross cost overruns. The 2008 United States Government and Accountability Office (GAO) review, in March 2008, revealed that the Navy was expecting the first two LCSs to exceed their budgets by more than 100 percent, while delivery of the first ship would be at least 18 months later than originally projected. These cost and schedule overruns led to the cancelled construction of the third and fourth LCSs. Funds originally allocated for construction of the fifth and sixth LCSs were allocated to pay for the extensive cost growth experienced by LCSs one and two (Littoral Combat Ship Program, 2008). Secretary of the Navy Donald Winter states: " . . . we recognize that active oversight and strict cost controls in the early years are necessary to ensuring we can deliver these ships to the fleet over the long term" (Scully, 2007). Inability to forecast the required cost for future ships and programs will not allow the Navy to reach its goal of a 313-ship Fleet by 2020.

Risk comes in various forms in the business of shipbuilding. Schedule, technology, source selection, and requirements are only a few of the factors that are associated with uncertainty and risk. The following statements, somewhat sarcastically, but with much insight, sum up potential impacts associated with risk in a project:

- "Any task can be completed in only one-third more time than is currently estimated." – Augustine's Law of Unmitigated Optimism, Law Number XXIII (Augustine, 1997).
- "The only thing more costly than stretching the schedule of an established project is accelerating it, which is itself the most costly action known to man." – Augustine's Law of Economic Unipolarity, Law Number XXIV (Augustine, 1997).

- “The process of competitively selecting contractors to perform work is based on a system of rewards and penalties, all distributed randomly.” – Augustine’s Law of the Phoenix, Law Number XXXIV (Augustine, 1997).
- “Ninety percent of the time things will turn out worse than you expect. The other 10 percent of the time you had no right to expect so much.” – Augustine’s Law of Apocalyptic Costing, Law Number XXXVII (Augustine, 1997).
- “One should expect that the expected can be prevented, but the unexpected should have been expected.” – Augustine’s Law of Amplification of Agony, Law Number XLV (Augustine, 1997).
- “The sooner you start to fall behind, the more time you will have to catch up” (Augustine, 1997).

B. HISTORY OF COST RISK ASSESSMENT

Gambling has been a human pastime for millennia and has been practiced at all levels of societies. Evidence of gambling can be found in Greek mythology, in which a game of “craps” was used to explain what we commonly refer to as the Big Bang. In Greek mythology, Zeus, Poseidon, and Hades rolled dice for parts of the universe. Zeus won the heavens, Poseidon the seas, and Hades became the master of the underworld (Bernstein, 1998).

Modern-day risk analysis has roots in the Hindu-Arabic numbering system as early as seven to eight hundred years ago. The new numbering system allowed writing to take the place of movable counters in making calculations. The act of being able to write calculations opened mathematics up to a new level. Risk analysis became a more serious topic during the Renaissance, in a time when people started to break free from past constraints and old beliefs to new challenges. In 1654, Chevalier de Mere challenged Blaise Pascal to answer a question that had been posed by Luca Paccioli over two hundred years prior. The problem was to determine how to divide the stakes of an incomplete game of chance between two different players when one of the players is ahead. In seeking out his answer, Pascal sought the help of Pierre de Fermat. Together

they came up with a solution to the Paccioli puzzle. This revelation led to the theory of probability, the heart of the concept of risk. Through this discovery, people could now make decisions and use numbers to forecast events in the future (Bernstein, 1998). In 1730, Abraham de Moivre discussed the structure of the normal distribution and developed the standard deviation (Bernstein, 1998). Both of these concepts are important components of modern day methods for conducting risk assessment.

Historically, cost growth has been associated with many large capital projects, especially those that have long construction periods. The trend has been that larger budgets and longer build times lead to greater risk and uncertainty. Figure 2 shows a history of cost growth over the last 700 years. This chart shows different reasons for which each of these major projects came in under, over, or right on cost estimates. An interesting note is that the Eiffel Tower project builder was guaranteed the first 20 years of revenue (Deegan, 2007b). This fact may have helped to influence the overall cost of the project to come in under budget. All of the causes listed in Figure 2 can be applied as reasons for problems with the accuracy of cost estimates in current shipbuilding projects. Being able to quantify cost variability and uncertainty is one way to help alleviate major cost overruns.

Possible Cause	Thames Tunnel	Eiffel Tower	Concorde	Suez Canal	Sydney Opera House	Channel Tunnel
Excessive Schedule Pressure	✓					✓
Changing Requirements			✓		✓	
Requirements Creep						
Limited Technical Specifications			✓			
New Technology	✓		✓		✓	✓
Insufficient Engineering Experience	✓		✓	✓		
Ignoring the Obvious	✓				✓	
Ignoring Test Results						
Political		✓	✓	✓	✓	✓
	+400%	-5%	+1200%	+2000%	N/A	+180%

Figure 2. Historical Cost Growth: Last 700 Years
(From: Deegan, 2007b)

C. CLASSICAL COST ESTIMATION AND CONTINGENCY PLANNING

Cost estimation is an analytical effort directed at calculating and predicting the cost of a system that involves several techniques such as data collection and analysis and risk analysis. It is a quantitative assessment of the most likely costs required to complete a project and always involves amounts of uncertainty and risk. The validity and significance of a cost estimate relies on the experience and judgment of those assigned with making the decisions involved in the estimate. There is no one correct answer when making a cost estimate as several factors must be taken into account in order to provide the best estimate for the given situation. Associated costs may include labor, material, equipment, inflation, and services. Cost estimators interact with many different personnel while collecting data for analysis. Consultation with SMEs, engineers, schedulers, accountants, statisticians, and mathematicians may occur in the cost estimation process (Project Manager's Body of Knowledge (PMBOK), 2004).

Classical cost estimation techniques involve using point estimates as the best value while also assigning a project contingency as a percentage of the total cost. This methodology is changing to the practice of using probability distributions to model cost without contingencies. Cost contingencies have been associated with overestimating costs to account for the contingency allowances. Program managers are responsible for the budget management of their projects and can benefit from using cost estimation techniques for use in budget planning and execution (Portny, Mantel, Meredity, Shafer, & Sutton, 2008).

D. PROBABILISTIC COST RISK ANALYSIS

Modern cost uncertainty analysis started in a field known as military systems analysis, which was founded in the 1950s at the RAND Corporation. The military systems analysis branch evolved after World War II and became a tool to aid defense leadership with decisions for force structure, composition, and theaters of operation. Naturally, cost analysis became an important part of the analysis models and decision process. Early cost uncertainty analysis focused on the sources, scope, and types of uncertainties that influenced the cost of future technologies. From 1955 to 1962, the

technical papers regarding cost uncertainty did not focus on developing formal methodologies to quantify cost uncertainty (Garvey, 2000). In the 1960s, a new focus on cost analysis had begun and forms the basis for today's cost estimation methods.

Cost estimation uncertainties are present in many elements of cost analysis. They originate from inaccuracies in models, misinterpretation of the models, misused cost analysis methodologies, economic uncertainties, requirements change, and system definition uncertainties. Cost risk analysis is the statistical treatment of the cost estimating process that considers the elements of the work breakdown structure (WBS) and total system costs as random variables. Cost analysis indicates that there is always some degree of risk that a system may not be delivered or meet required objectives at a certain funding level. One of the goals of cost analysis is to be able to assign a degree of confidence to any particular estimate of a system cost. Another factor to consider when conducting cost risk assessment is to analyze what funding level percentage is appropriate for the project.

Most cost estimation is based on historical data obtained from SMEs and databases from previously built systems. Basing a cost estimate on past systems can be tricky and complicated. Cost analysts have been expected to provide a best estimate of cost for various options at milestones and decision points in the acquisition of major weapons programs. What precisely is the best estimate? Definitions of the term "best estimate" vary with different projects, and with each analyst and program manager. The best estimate may be the most likely cost, the median, or the average cost. The term "best estimate" implies that other less likely solutions may exist.

In probabilistic or risk cost estimation, costs of each WBS element are modeled with probability distributions and then correlations among these elements are estimated. The result of the correlated distributions is statistically summed by using a simulation such as Monte Carlo. The simulation results in the total system cost represented by a probability distribution. Estimates of statistical parameters, such as the median or other pertinent values, can be extracted from the final probability distribution. These values are meaningful to program managers and decision makers when establishing program budgets.

Cost estimation can also be used as a decision aid when program managers need to make a decision about the appropriate funding level for a project. Figure 3 shows the impact of either budgeting with a value less or greater than the mean. Both decisions have possible positive and negative outcomes. It is important for the program manager and budget decision makers to have the most complete understanding of the cost analysis and consequence to make the best budget decisions.

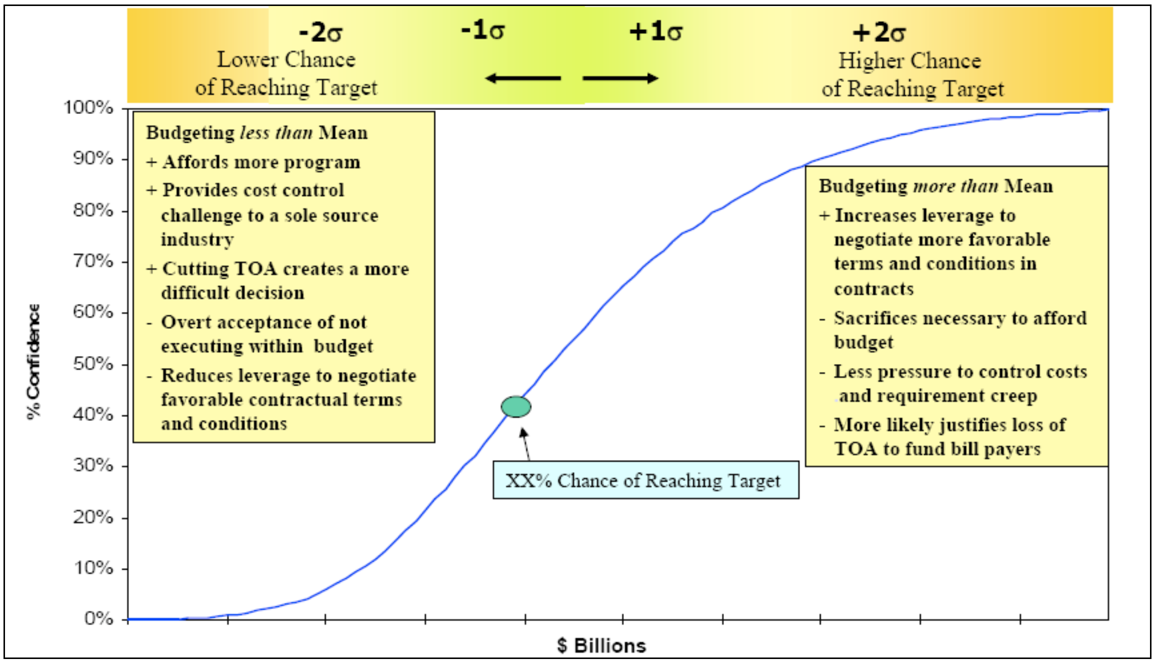


Figure 3. Business Rules to Consider: Choosing an acceptable cost risk point requires an understanding of consequence (From: Deegan, 2007b).

Figure 4 is a flowchart that represents the basic steps in estimating probable systems cost (Book, 2001). This thesis focuses on the "Probability Distributions, Perform Monte Carlo Simulations, Cumulative Distribution, and Read Off Cost Percentiles" blocks of this process within the Cost-Risk Analysis branch.

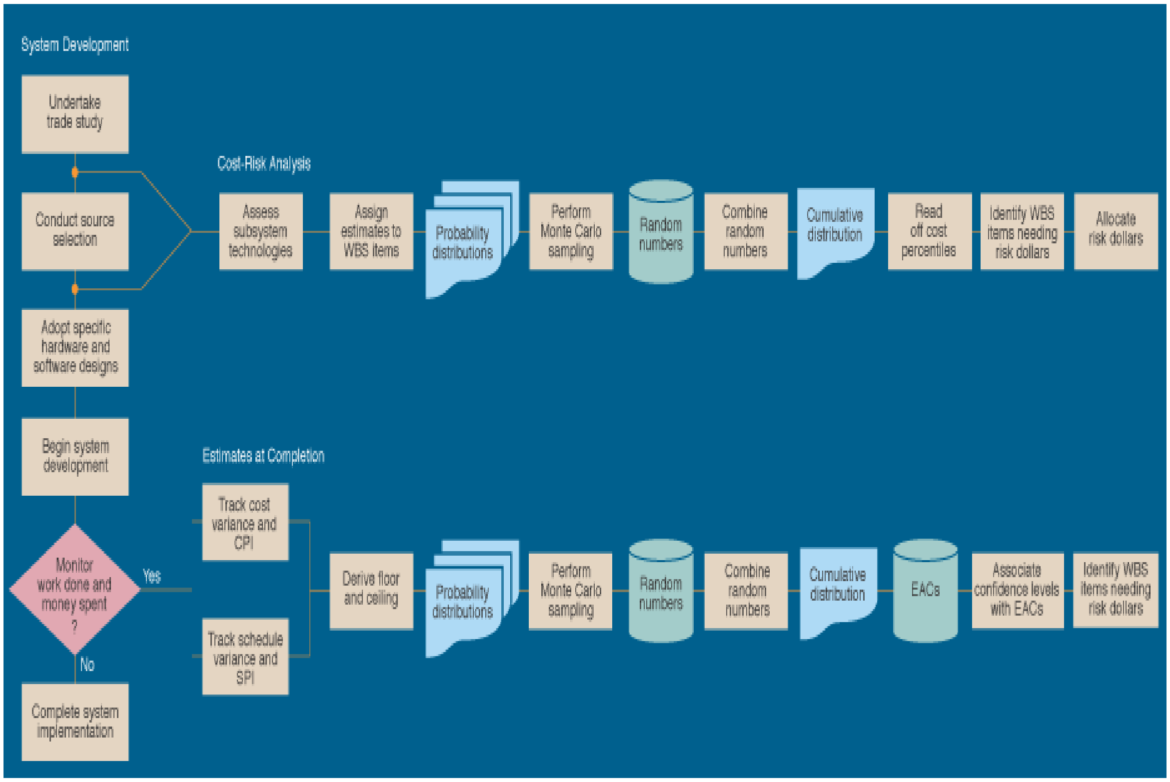


Figure 4. Basic Steps in Estimating Probable Systems Cost (From: Book, 2001)

E. CHAPTER SUMMARY

There is an ongoing major shift in research and development and complex engineering projects from deterministic to probabilistic approaches. Probabilistic cost risk analysis provides the proper framework for handling the many different factors that contribute to cost uncertainties. It is an important tool for program managers to use in making better budget decisions. This is especially significant for the today's Navy during a time of budget hardship. In order for the Navy's plans for a 313-ship Fleet to become a reality, the incorporation of cost risk analysis into the aspects of acquisition and shipbuilding is imperative. Cost assessment can help to deliver projects on time, at a lower cost, with a higher probability of success. Effective training of personnel involved in cost assessment, and continued efforts to improve on existing models will help to more fully integrate this way of doing business into the current cost estimating process.

THIS PAGE INTENTIONALLY LEFT BLANK

III. REVIEW OF THE NAVSEA 05C (COST ENGINEERING AND INDUSTRIAL ANALYSIS DIVISION) COST RISK MODEL

A. INTRODUCTION

The cost model used for analysis in this thesis was obtained from NAVSEA 05C. Mr. Chris Deegan, the former Director of the Naval Sea Systems Command Cost Engineering and Industrial Analysis Division, and Mr. Aaron Ratliff, his CG(X) analyst, provided the model. The model contains information required to determine the cost of an entire CG(X) ship including economic factors such as inflation, profit, and learning curves for the complete CG(X) fleet. Because of the complexity of the model, this thesis focuses on the electronics cost portion and the effects of data elicitation, probability distribution choice, correlation effects, and the MAIMS principle on the probabilistic costs associated with technology, design, engineering, production, testing, and integration risks for the first vessel.

B. REVIEW OF CG(X) SHIP CLASS AND MODELS

The CG(X) ship is designed to be the future Fleet's replacement for the Ticonderoga Class AEGIS Cruisers. New technologies being advocated and presented in CG(X) include a stealthier hull form, improved missiles, integrated power systems, and advanced radar systems (Navy of the Future, 2008). To lessen costs, the CG(X) was to share many common features with DDG 1000. As of July 2008, only two of the DDG 1000 ships will be built due to funding constraints. This is a significant reduction from the original 32-ship DDG 1000 plan of the 1990s (Cavas, 2008a). These same funding constraints place an important emphasis on effective cost and risk modeling for CG(X), to help ensure that its acquisition is not put in jeopardy due to unforeseen cost issues.

The NAVSEA CG(X) cost model uses historical data from DDG 1000 expressed in FY2005 dollars. It comprises 63 separate worksheets within the main Excel® workbook. The data used in this model consists of inputs from SME inquiry, historical data from past shipbuilding projects, historical data from shipyard figures, and historical

rate data. The NAVSEA 05C CG(X) cost model takes into account all factors involved in cost for every aspect of the ship including labor rates, material cost, overhead cost, planning cost, production cost, engineering cost, construction cost, change orders, electronics cost, hull, mechanical and engineering costs, and ordnance. Figure 5 is the Cost Placemat of the NAVSEA 05C CG(X) model, which shows how the cost breakdown is established.

***All Costs expressed in FY05 $ (excep

MAMDJF/CG(X) - DDG 1000 Based - X1

	FY11	FY18	FY18	FY18
Schedule	Lead	5th Follow Yard A	5th Follow Yard B	Average Follow
Award Date	Jan-11	Jan-18	Jan-18	Jan-18
Start Construction Date	Jan-13	Jul-19	Jul-19	Jul-19
Delivery Date	Jan-17	Jan-23	Jan-23	Jan-23

P-5 Summary ($M)	Lead	5th Ship Yard A	5th Ship Yard B	Average Follow
Plans	$ 258	$ 51	$ 31	$ 41
Basic Construction	$ 1,126	$ 976	$ 1,207	$ 1,091
Change Orders	$ 113	$ 49	$ 60	$ 55
Electronics	$ 766	$ 549	$ 548	$ 549
HM&E	$ -	$ -	$ -	$ -
Other	$ 103	$ 93	$ 93	$ 93
Ordnance	$ 97	$ 76	$ 76	$ 76
Escalation	$ -	$ -	$ -	$ -
Total	**$ 2,463**	**$ 1,793**	**$ 2,015**	**$ 1,904**
Post Delivery / Outfitting				

Hours M	Lead	5th Ship Yard A	5th Ship Yard B	Average Follow
Production	7.70	6.70	7.45	7.08
Engineering	1.58	1.10	1.53	1.32
Total	9.28	7.80	8.98	8.39
Detailed Design	2.65	-	-	-

Rates	Lead	5th Ship Yard A	5th Ship Yard B	Average Follow
Production	$28.30	$36.03	$41.26	$ 38.65
Engineering	$33.34	$42.44	$45.40	$ 43.92
Plans	$34.17	$ -	$ -	$ -
Production OHD	149%	149%	211%	180%
Engineering OHD	136%	136%	105%	120%
Plans OHD	96%	0%	0%	0%
Fully Burdened Rate				

	Lead	5th Ship Yard A	5th Ship Yard B	Average Follow
Labor ($M)	$ 590	$ 498	$ 685	$ 591
Material ($M)	$ 377	$ 340	$ 353	$ 346
COST	**$ 967**	**$ 838**	**$ 1,038**	**$ 938**
FCCM ($M)	$ 15	$ 13	$ 14	$ 14
Profit ($M) [15%]	$ 144	$ 124	$ 154	$ 139
BASIC PRICE ($M)	**$ 1,126**	**$ 976**	**$ 1,207**	**$ 1,091**
Change Orders ($M)	$ 113	$ 49	$ 60	$ 55

	Lead	**Total Follow (**	**Total Program**
Cost Constraint	$ 2,600	$ 43,200	$ 45,800
X1 Point Estimate	$ [illegible]	$ [illegible]	$ [illegible]
X1	$ 2,778	$ 35,296	$ 38,075
Delta	$ 178	$ (7,904)	$ (7,725)

LEAD YARD - **Yard A**

Design Weights

	X1 (DDG 1000 5.X)	DDG1000 5.X
Weight Report Dated:	Dec. 6, 2006	
Light Ship Displacement (LT)	11,783	12,523
Light Ship Displacement w/ Margin (LT)	12,797	13,126
Full Load Displacement	14,566	15,004
SWBS 100	6,200	6,488
SWBS 200	1,118	1,118
SWBS 300	1,400	1,380
SWBS 400	655	645
SWBS 500	1,257	1,249
SWBS 600	737	738
SWBS 700	415	903
Design & Build Margin (less Inclining)	1,014	603

Key Assumptions

Profit:		15%	
Change Orders:	Lead:	10%	
	Follow:	5%	
FCCM	Yard A:	8.70%	Prod.
		1.00%	Eng.
	Yard B:	6.00%	

References

GFE Dated:	
Global Insight Dated:	2006, 4th Quarter
SEA 017 Factor Program Dated:	Feb, 2007

Learning Curve

Learning Curve Slope		
	Yard A:	92%
	Yard B:	93%
Starting T-Unit	Yard A	T2
	Yard B:	T2
	Leadship adder of 5%	

Figure 5. NAVSEA 05C CG(X) Cost Model: Cost Placemat showing cost breakdown.

Figure 6 shows a section of the Mission Systems Risk Assessment worksheet of the NAVSEA 05C CG(X) Excel® workbook. This worksheet shows the different cost elements of the WBS for the electronics suite of CG(X) as well as the WBS elements for the ordnance suite. The elements of the ordnance suite are not considered in this thesis. This figure is a snapshot of a single step of the Monte Carlo simulation. Note that

X1(Rec) was generated as part of the thesis using the Excel® spreadsheets provided by NAVSEA 05C. The column “X1 (Rec)” represents the random variables corresponding to the recurring costs of the first ship of the class. It corresponds to the probabilistic costs, which include uncertainty information. The values for the X1 costs are calculated using the subsystem cost values provided by the Input Template worksheet shown in Figure 7. The column showing nonrecurring engineering (NRE) costs are costs for only the lead ship of the class. The values in the “most likely” column are point estimates with the “low” and “high” values as the upper and lower cost bounds of the individual electronics suite elements.

The Naval Surface Warfare Center (NSWC), Dahlgren, Virginia, provided the low, most likely, and high values for the system and component costs. These values provide the basic input for this thesis. The electronics values and how they are determined are the focus of this thesis.

MAMDJF AoA Lead Ship Production Cost Estimate Risk Analysis

All Costs Reported in Year of award

X1 (Lead Ship) (TY11$M)								
WBS	NRE	X1 (Rec)	% Low	Low	Most Likely	High	% High	Distribution
Ordnance	**$ 14.70**	**$107.84**		**$ 86.30**	**$ 93.77**	**$ 165.74**		**Extreme**
VLS	$ 3.20	$70.93	95%	$ 58.60	$ 61.68	$ 101.57	165%	Triangular
CIGS	$ 11.500	$ 31.97	85%	$ 23.63	$ 27.80	$ 55.60	200%	Extreme
DLS	$ -	$ 4.93	95%	$ 4.07	$ 4.29	$ 8.58	200%	Extreme
Electronics	**$ 160.38**	**$ 804.53**		**$ 633.57**	**$ 748.19**	**$ 910.20**		
Radar Suite	**$ 23.15**	**$ 257.49**	**85%**	**$ 190.32**	**$ 223.90**	**$ 257.49**	**115%**	
X-band	$ -	$ 65.58	95%	$ 62.30	$ 65.58	$ 75.41	115%	Triangular
S-band	$ 22.72	$ 154.61	95%	$ 146.88	$ 154.61	$ 177.80	115%	Triangular
Cooling	$ 0.43	$ 3.71	95%	$ 3.53	$ 3.71	$ 4.27	115%	Triangular
Power (included in Ship Total)	$ 1.82	$ 55.89	95%	$ 46.17	$ 48.60	$ 55.89	115%	Triangular
ExComm	$ 30.21	$ 154.44	75%	$ 100.72	$ 134.29	$ 188.01	140%	Triangular
TSCE	$ 3.45	$ 86.61	75%	$ 56.49	$ 75.32	$ 94.15	125%	Normal
IUSW	$ 5.69	$ 30.38	95%	$ 25.09	$ 26.41	$ 27.73	105%	Normal
EW-IW	$ 21.02	$ 56.10	75%	$ 36.58	$ 48.78	$ 60.97	125%	Normal
EO-IR	$ -	$ 14.15	95%	$ 11.69	$ 12.31	$ 12.92	105%	Normal
IFF	$ -	$ 9.65	95%	$ 7.98	$ 8.40	$ 8.82	105%	Normal
MS EI&T (SS Only)	$ 60.89	$ 105.19	80%	$ 73.18	$ 91.47	$ 109.77	120%	
MS EI&T (CS Only)	$ 15.98	$ 90.52	80%	$ 62.97	$ 78.71	$ 94.45	120%	
ATP	*$ -*	*$ 1.38*	*95%*	*$ 1.31*	*$ 1.38*	*$ 1.45*	*105%*	*Normal*

Figure 6. NAVSEA 05C CG(X) Model - Section of Mission Systems Risk Assessment worksheet depicting WBS Ordnance and Electronics Suite elements. It captures a snapshot of a single step of Monte Carlo simulation run using Crystal Ball®.

Figure 7 shows a section of the Input Template worksheet from the NAVSEA 05C CG(X) model. As indicated by the "Distribution Used" column, NAVSEA 05C uses a lognormal distribution for each cost component in the electronics suite. It then characterizes each lognormal distribution in terms of the mean and standard deviation values given in the Risk Ranges Mission Systems worksheet, a section of which is shown in Figure 8. Analysis of the provided data appears to indicate that NAVSEA 05C computes the mean and standard deviation values treating the "low," "most likely," and "high" values as a discrete, rather than a triangular, distribution. This calculation of the standard deviation and mean for the lognormal distribution has not been confirmed with NAVSEA 05C. This approximation provides values significantly different from those based on a triangular distribution, as is typically done in today's de facto probabilistic cost analysis. NAVSEA 05C introduces an additional approximation and treats the radar suite as a single composite cost, rather than in terms of its individual cost elements.

Input Template (Solutions)

Risk Factors for Ship X	Units	Base Value	Distribution Used	Distr. Parameter 1	Distr. Parameter 2
Mission Systems					
VLS	%	100%	LogNormal	120%	35%
Rationale				Mean	St Deviation
CIGS	%	100%	LogNormal	100%	15%
Rationale				Mean	St Deviation
DLS	%	100%	LogNormal	132%	45%
Rationale				Mean	St Deviation
Radar Suite	%	100%	LogNormal	101%	17%
Rationale				Mean	St Deviation
ExComms	%	100%	LogNormal	105%	35%
Rationale				Mean	St Deviation
SEI&T	%	100%	LogNormal	100%	26%
Rationale				Mean	St Deviation
TSCE	%	100%	LogNormal	100%	26%
Rationale				Mean	St Deviation
IUSW	%	100%	LogNormal	100%	9%
Rationale				Mean	St Deviation
EW-IW	%	100%	LogNormal	100%	35%
Rationale				Mean	St Deviation
EO-IR	%	100%	LogNormal	100%	16%
Rationale				Mean	St Deviation
IFF	%	100%	LogNormal	100%	13%
				Mean	St Deviation

Figure 7. NAVSEA 05C CG(X) Model- Section of the Input Template worksheet depicting the systems analyzed in this thesis.

Recurring

VLS

	Low	Most Likely	High	Average	Std Deviation	
	$ 58.60	$ 61.68	$ 101.57	74	24	<----- due to bias
%Std	12%	10%	20%	10%	13%	
Std Dev	7.031573242	6.1680467	20.313214	7	9	<----- due to estimate variability incl. Correlation
				74	26	<----- due to estimate variability + bias
					35%	

Enter Estimated Correlations among variables (0-None, .2-some, .5-moderate, 1.0-perfect), positive or negative

Correlation	1	2	3
1	1	0.2	0.2
2	0.2	1	0.8
3	0.2	0.8	1

EW-IW

	Low	Most Likeli	High	Average	Std Deviatio	Note: For EW-IW, Single Est. Only, assume +-25%
	$ 36.58	$ 48.78	$ 60.97	49	12	<----- due to variance within one estimate
%Std	25%	25%	25%	15%	25%	
Std Dev	9.1461001	12.1948	15.2435	7	12	<----- due to estimate variability incl. Correlation
				49	17	<----- due to estimate variability + bias
					35%	

Enter Estimated Correlations among variables (0-None, .2-some, .5-moderate, 1.0-perfect), positive or negative

Correlation	1	2	3
1	1	1	1
2	1	1	1
3	1	1	1

EO-IR

	Low	Most Likeli	High	Average	Std Deviatio	Note: For EO-IR, Single Est. Only, assume +-25%
	$ 11.69	$ 12.31	$ 12.92	12	1	<----- due to variance within one estimate
%Std	15%	15%	15%	9%	15%	
Std Dev	1.7535267	1.845818	1.93811	1	2	<----- due to estimate variability incl. Correlation
				12	2	<----- due to estimate variability + bias
					16%	

Enter Estimated Correlations among variables (0-None, .2-some, .5-moderate, 1.0-perfect), positive or negative

Correlation	1	2	3
1	1	1	1
2	1	1	1
3	1	1	1

IFF

	Low	Most Likeli	High	Average	Std Deviation	
	$ 7.98	$ 8.40	$ 8.82	8	0	<----- due to bias
%Std	15%	15%	15%	9%	12%	
Std Dev	1.1963313	1.259296	1.32226	1	1	<----- due to estimate variability incl. Correlation
				8	1	<----- due to estimate variability + bias
					13%	

Enter Estimated Correlations among variables (0-None, .2-some, .5-moderate, 1.0-perfect), positive or negative

Correlation	1	2	3
1	1	0.5	0.5
2	0.5	1	0.5
3	0.5	0.5	1

Figure 8. NAVSEA 05C CG(X) Model - Risk Ranges Mission Systems worksheet.

C. DATA SELECTED FOR FURTHER ANALYSIS

This thesis uses the low, most likely, and high data values, which are provided by the Mission Systems Risk Analysis worksheet shown in Figure 6. The Mission Systems Risk Analysis worksheet is one of the 63 worksheets of the CG(X) model. The X1(Rec) value is derived from data contained in other worksheets in the model. The details of the methodology of how the X1(Rec) value is developed is outside the scope of this thesis. This thesis then evaluates the impact of different distributions, data elicitation, correlations, and the MAIMS principle on the estimated cost.

The thesis investigates the following probability distributions:

- Triangular distributions using specified high, most likely, and low values.
- Lognormal using the mean and standard values from the triangular distributions.
- Two sets of Weibull distributions using the triangular distribution parameters as different percentiles to reflect data elicitation.
- One set of Weibull distributions modified to account for the MAIMS principle.

It also investigates correlation effects using a two-parameter model (Kujawski et al., 2004).

A discussion of data elicitation practices and methods is presented, and its impact on the quality of data is explored. Data elicitation can directly affect the choice of distribution used to realistically evaluate cost. Data that is elicited using proven methods and/or based on historical data give more realistic and credible predictions than data that is simply a best guess. This is where the importance of data elicitation from the SME can make a dramatic impact on the quality of data obtained for use in the model. Augustine sums up the impact of poor data:

> The weaker the data available upon which to base one's conclusion, the greater the precision which should be quoted in order to give the data authenticity. – Augustine's Law of Definitive Imprecision, Law Number XXXV (Augustine, 1997).

The final analysis of this thesis involves the investigation of the impact of modifying the Weibull distributions to simulate the MAIMS principle, assuming the project will spend all money allocated and not have a cost underrun.

D. CHAPTER SUMMARY

The NAVSEA 05C's cost analysis model of CG(X) encompasses all aspects of cost for the entire fleet including inflation and profit in a 63 worksheet Excel® workbook. The data used in the NAVSEA model were acquired from SME inquiry using three-point estimates of high, most likely, and low values. The Navy is placing great emphasis on producing the best product for each dollar spent. In order to ensure the continued acquisition of CG(X), it is important that realistic cost risk analysis be performed so that program managers can make informed decisions.

Chapter IV presents an approach to improve on the model that NAVSEA 05C has provided for CG(X). The focus is strictly on the methodology used in the cost analysis of the electronics suite of CG(X), represented in the Mission Systems Risk Assessment spreadsheet of the model.

THIS PAGE INTENTIONALLY LEFT BLANK

IV. REVISED COST RISK ANALYSIS

A. INTRODUCTION

This thesis specifically looks at the electronics portion of the CG(X) cost model and cost uncertainties associated with engineering and manufacturing of the lead vessel. Nine systems make up the electronics suite:

- Radar suite, which consists of the following subsystems: X-band, S-band, Cooling, and Power
- ExComm – External Communications
- TSCE – Total Ship Computing Environment
- IUSW – Integrated Undersea Warfare
- EW-IW – Electronic Warfare-Information Warfare
- EO-IR – Electro Optical-Infrared
- IFF – Identification, Friend or Foe
- MS EI&T (SS Only) – Mission Systems Engineering, Integration, and Testing (Ship Systems Only)
- MS EI&T (CS Only) – Mission Systems Engineering, Integration, and Testing (Combat Systems Only)

The electronics suite cost is determined with the following two equations that treat each of the cost elements as a random variable (RV). The costs in bold represent composite of the costs in regular font, which Crystal Ball® refers to as forecasts and assumptions:

COST(Electronics Suite) = **COST(Radar Suite)** + COST(ExComm) + COST(TSCE) + COST(IUSW) + COST(EW-IW) + COST(EO-IR) + COST(IFF) + COST(MS EI&T (SS Only)) + COST(MS EI&T (CS Only)),

Cost(Radar Suite) = Cost(X-band) + Cost(S-band) + Cost(Cooling) + Cost(Power).

The steps of analysis for the CG(X) model are:

1. Analyze the cost factors used by NAVSEA 05C to develop the electronics suite cost.
2. Analyze the PDFs used for the electronics cost elements.
3. Identify what data elicitation methods were employed.
4. Determine if correlation factors were used in the cost analysis.
5. Develop cost factors to be modeled for cost realism.
6. Decide which PDFs to use for greater fidelity.
7. Develop an improved cost risk model that includes realistic correlation factors; credible PDFs, including MAIMS influences; and SME biases.

B. REVIEW DEVELOPMENT OF COST FACTORS

The cost factors used in the NAVSEA05C CG(X) cost model for the electronics suite in this thesis include data elicitation methods, PDF choice, correlation effects, and MAIMS Principle effects. This research does not pursue the other elements of cost such as labor, material, or inflation rates that NAVSEA 05C models.

1. Data Elicitation Methods

The data elicitation methods used by NAVSEA 05C cost analysts are not well documented. It is clear that the engineering and expert judgment of SMEs is heavily relied on for the assessment of uncertain cost elements associated with new designs. This is an area where the use of improved methods can dramatically improve the quality of data that is used in the computation of the cost risk model. Subjective assessments to obtain data have been identified as a critical source of uncertainty in probabilistic risk analyses (Keeney & von Winterfeld, 1991). Kujawski et al. (2004) discuss the use of the

DFA method for data elicitation and how this ties in with distribution choice, to provide the most realistic cost assessment.

DFA has been found to provide one of the most consistent and least bias-prone methods for eliciting uncertain quantities (Alpert & Raiffa, 1982). In their research, people were asked to consider uncertain quantities by providing values in terms of percentiles or fractiles. The findings indicated:

- There is a systematic bias toward overconfidence in estimates. The subjective probability distributions were too narrow. Usually, 33% instead of 50% of the actual values fell within the 0.25 to 0.75 fractiles.
- Extreme value judgment is even worse. Twenty percent, rather than 2%, of the actual values fell outside the 0.01 and 0.99 fractiles.
- What is the meaning of minimum and maximum values? Defining these terms, so that they are universal, is difficult.

Kujawski et al. (2004) further suggest using experts to provide the 10th, 50th, and 90th percentile values, as these may be easier to assess than extreme values of maximum and minimum. They recommend avoiding asking for extreme values, abstract values such as the mean or standard deviation, or other specific distribution functions. If the analyst does not fully understand the background of the questions being asked to obtain data, or if he does not fully understand the behavior of the system and associated data, obtaining discrete values will be near impossible.

Education also plays an important role in the quality of the data provided by the SMEs for analysis. The understanding of bias and its role in affecting data elicitation is important. In a presentation to the Navy Cost Analysis Symposium, Fields and Popp (2007) stress the importance of several lessons learned on risk. One of the most interesting of these lessons learned is the importance of training. They indicate that although NAVSEA and its technical community have a broad cross section of educational backgrounds and experience, this does not mean that everyone has experience in simulation and statistics. The SME for a particular electronics suite component is probably not an expert in probability and statistics, and because of this,

tends to give biased answers to the cost analysis. The distributions formed from the biased data have been found to be particularly narrow and centered on a given point estimate, while the extreme values are very rarely taken into account, for reasons described above.

Education of the SMEs while conducting data elicitation is important, so that the experts have a better understanding of what data is required and how it is going to be utilized. This training needs to be continually refreshed due to the high turnover rate of personnel, whether they be military or civilian, and also because of improving methods for cost analysis. An adequate training plan for both the cost analysts and the SMEs providing data will ultimately result in better data acquisition for cost analysis.

In this thesis, the use of DFA is simulated though the use of Weibull probability distributions because no new data elicitation was conducted. The differences between the distributions using identical values for 10th, 50th, and 90th percentiles versus the 20th, 50th, and 80th percentiles illustrates data elicitation that is optimistic versus pessimistic. The resulting cost associated with each of the two distributions shows how dramatic the effects of slightly different parameters can have on the estimated cost.

2. Choice and Development of Probability Distribution Functions

Kujawski et al. (2004) emphasize the importance of realistically modeling cost uncertainties through the appropriate choice of probability distribution by meeting the following criteria:

- Capable of fitting three arbitrary percentiles.
- A finite lower range.
- An infinite upper range with reasonable behavior.
- Physically meaningful and easy to estimate parameters.

Three types of PDFs are developed and modeled for this thesis, with the goal of finding a realistic and flexible probability distribution. Uncertainty for each cost element in the cost model is represented using the same type of PDF with different parameters (based on NAVSEA data). First, a triangular PDF that uses low, most likely, and high values for its parameters is developed. A lognormal PDF that uses the mean and standard deviation from the triangular PDF as its parameters is the second distribution. The third

PDF is a three-parameter Weibull distribution based on the low, most likely, and high values of the triangular PDF provided by NAVSEA 05C. The low and high values are calculated by multiplying the low and high percentages obtained with the most likely value shown in Figure 6. Two Weibull distributions are created. One of the Weibull distributions uses the data as input for the 10th, 50th, and 90th, percentiles, while the other is more pessimistic and uses these values for the 20th, 50th, and 80th percentiles. The data for these parameters is taken from the Mission Systems Risk Assessment worksheet (see Figure 6). For consistency, the triangular distribution is used to determine the 50th percentile. The low, 50th percentile, and high values are substituted for the 20th, 50th, and 80th percentiles and for the 10th, 50th, and 90th, for each three-parameter Weibull distribution, respectively. Table 2 shows the values that were used for the parameters of each probability distribution function for the different electronics suite elements. Crystal Ball® determines the three-parameter Weibull distribution by using the specified three percentiles. For example, the parameters of the Weibull (10%, 50%, 90%) distribution for the X-Band element are: location = 60.02, scale = 9.21, and shape = 1.61. For thoroughness, I verified that Crystal Ball® generates identical distributions using three percentiles and the three standard Weibull parameters.

	A	B	C	D	E	F	G	H	I	J	K	L
1		Distributions										
2		Triangular			Lognormal	Triangular	Weibull (10, 50, 90)			Weibull (20, 50, 80)		
3	WBS	Low	Most Likely	High	Mean	Standard Deviation	10%	50%	90%	20%	50%	80%
4	X-band	$62.30	$65.58	$75.41	$67.76	$2.78	$62.30	$67.36	$75.41	$62.30	$67.36	$75.41
5	S-band	$146.88	$154.61	$177.80	$159.83	$6.56	$146.88	$158.90	$177.80	$146.88	$158.90	$177.80
6	Cooling	$3.53	$3.71	$4.27	$3.84	$0.16	$3.53	$3.82	$4.27	$3.53	$3.82	$4.27
7	Power (included in Ship Total)	$46.17	$48.60	$55.89	$50.24	$2.06	$46.17	$49.95	$55.89	$46.17	$49.95	$55.89
8	ExComm	$100.72	$134.29	$188.01	$141.19	$18.12	$100.72	$139.89	$188.01	$100.72	$139.89	$188.01
9	TSCE	$56.49	$75.32	$94.15	$75.29	$7.67	$56.49	$75.33	$94.15	$56.49	$75.33	$94.15
10	IUSW	$25.09	$26.41	$27.73	$26.42	$0.54	$25.09	$26.41	$27.73	$25.09	$26.41	$27.73
11	EW-IW	$36.58	$48.78	$60.97	$48.68	$5.03	$36.58	$48.63	$60.97	$36.58	$48.63	$60.97
12	EO-IR	$11.69	$12.31	$12.92	$12.31	$0.25	$11.69	$12.31	$12.92	$11.69	$12.31	$12.92
13	IFF	$7.98	$8.40	$8.82	$8.40	$0.17	$7.98	$8.40	$8.82	$7.98	$8.40	$8.82
14	MS EI&T (SS Only)	$73.18	$91.47	$109.77	$91.61	$7.55	$73.18	$78.85	$109.77	$73.18	$78.85	$109.77
15	MS EI&T (CS Only)	$62.97	$78.71	$94.45	$78.77	$6.45	$62.97	$91.67	$94.45	$62.97	$91.67	$94.45

Table 2. Parameters used in the probability distribution functions for the different electronics suite elements.

a. Triangular Probability Distribution Function

The parameters used to develop the triangular PDF are the low, most likely, and high values from the Mission Systems Risk Assessment worksheet (Figure 6). The determination of the high and low percentages for cost values in the Mission Systems Risk Assessment worksheet were figures given to NAVSEA 05C cost analysts by SMEs from the NSWC Dahlgren. These percentages are based on historical database values and inquiry of the SME for an opinion about what they thought the low and high values would be, based on the most likely values obtained from the historical databases. In this case, data elicitation plays a big part in the reliability of the data used in the model, which is be described in more depth in Section IV.B.1.

The triangular distribution is not a good predictor of high and low costs because it uses the low and high values as extreme values for the end points. There is no allowance for costs above or below the input values. It has been argued that a triangular distribution can lead to either underestimates or overestimates. Graves (2001) states that underestimates are likely due to the finite upper limit of the distribution. Moran (1999) believes that overestimates happen because of the distribution's inability to portray the expert's confidence level of achieving the most likely value and/or knowledge of the shape of the distribution. The triangular distribution is assigned a very low score for criteria (i) and (iii) (Kujawski et al., 2004) and is not the chosen distribution to represent cost in the model for this thesis.

b. Lognormal Probability Distribution Function

The lognormal PDF is created with the mean and standard deviation parameters taken from the triangular distribution. Characteristics of a lognormal distribution include being positively skewed with a limitless upper bound and known lower bound. This distribution is assigned an acceptable score for criteria (iii), but a low score for (i), due to the always positively skewed nature of the distribution. The lognormal distribution results in a cost profile that closely follows with the triangular distribution, and is one of the narrowest profiles modeled. A lognormal PDF has been associated with providing unreasonably high probabilities at high values, due to the

relatively slow falloff to the right. For this reason, it gets an acceptable score for the criteria (iii), but scores low on the criteria (i) because of its always positively skewed characteristic (Kujawski et al., 2004).

c. Weibull Probability Distribution Function (10%, 50%, 90%)

The three-parameter Weibull distribution is characterized by being flexible and able to assume a wide variety of shapes, while also being open-ended. Because of its flexible profile and ability to mimic other distributions, it scores high on all criteria.

This thesis models one of the three-parameter Weibull distributions with the 10th, 50th, and 90th percentile values for cost. The parameters of 10th, 50th, and 90th percentiles are chosen to simulate a cost environment that allows for some cost flexibility on the upper and lower limits rather than making them extreme as in the triangular distribution. Although this 10% change on either side of the distribution seems large, it actually represents a fairly optimistic assessment of cost. This model is best for a situation in which the data obtained for the model is very reliable.

d. Weibull Probability Distribution Function (20%, 50%, 80%)

The three-parameter Weibull distribution using the 20th, 50th, and 80th percentiles for distribution parameters is intended to correct or account for the overly optimistic biases discussed in Section 2 above. Systems that are new and untested have a certain amount of uncertainty inherent in their acquisition, and most cost assessments made on their components are based on past history if components are being reproduced, or a best estimate for new systems and their components. SMEs are naturally optimistic about their systems and have been shown to give cost estimates that are overconfident, resulting in probability distributions that do not accurately reflect the possible range of costs (Kujawski et al., 2004).

Much data for the CG(X) electronics suite is the result of inquiry of SMEs and because of this, the Weibull distribution using 20%, 50%, and 80% parameters is chosen to model costs for the electronics suite components in this thesis.

e. Cost Comparisons with the Different Probability Distributions

Figure 9 is the Excel® overlay created with Crystal Ball® that shows of a 10000-run Monte Carlo simulation for the triangular, lognormal, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%) distributions, representing the electronics suite cost of the CG(X). Figure 10 is the cumulative probability distribution derived from the PDF shown in Figure 9. The triangular and lognormal distributions are very similar in both the probability distribution and cumulative frequency functions, which is expected. Since the lognormal distribution uses the mean and standard deviation from the triangular distribution as its parameters, the end result should be very similar. Both the triangular and lognormal functions show a very distinct peak and sharp falloff at both the lower and upper bounds. This behavior does not realistically model the electronics suite cost because of the sharp peak with sharp falloff.

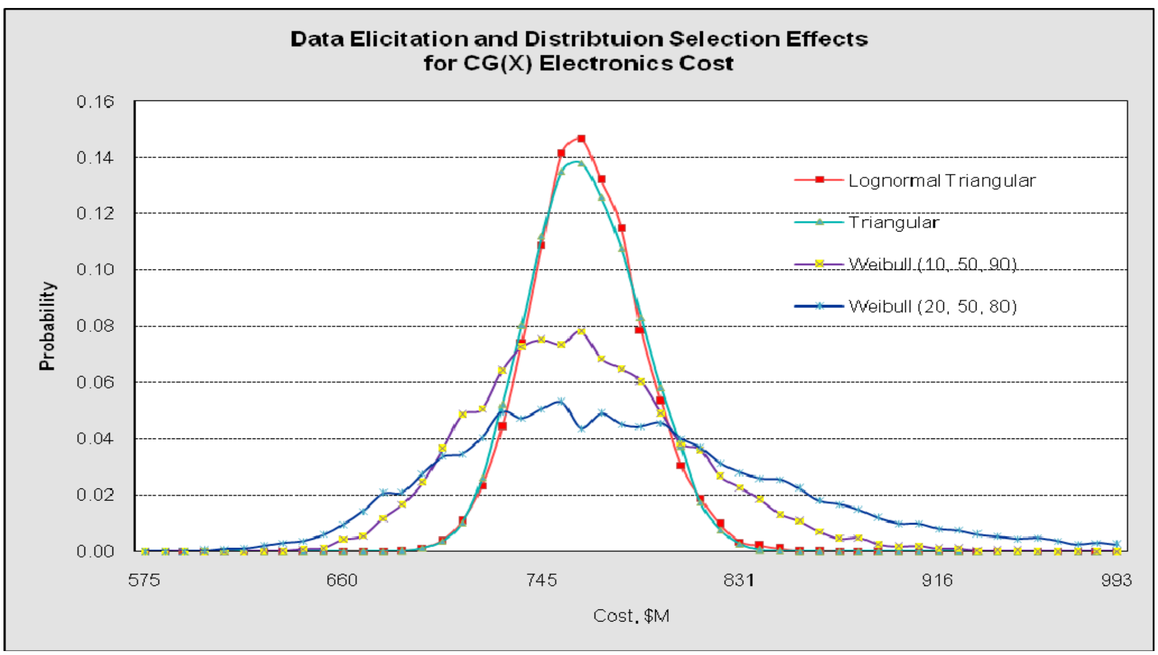


Figure 9. CG(X) Crystal Ball® Analysis, 10000 Runs showing the Effects of Distribution Choices on the Cost probability distributions.

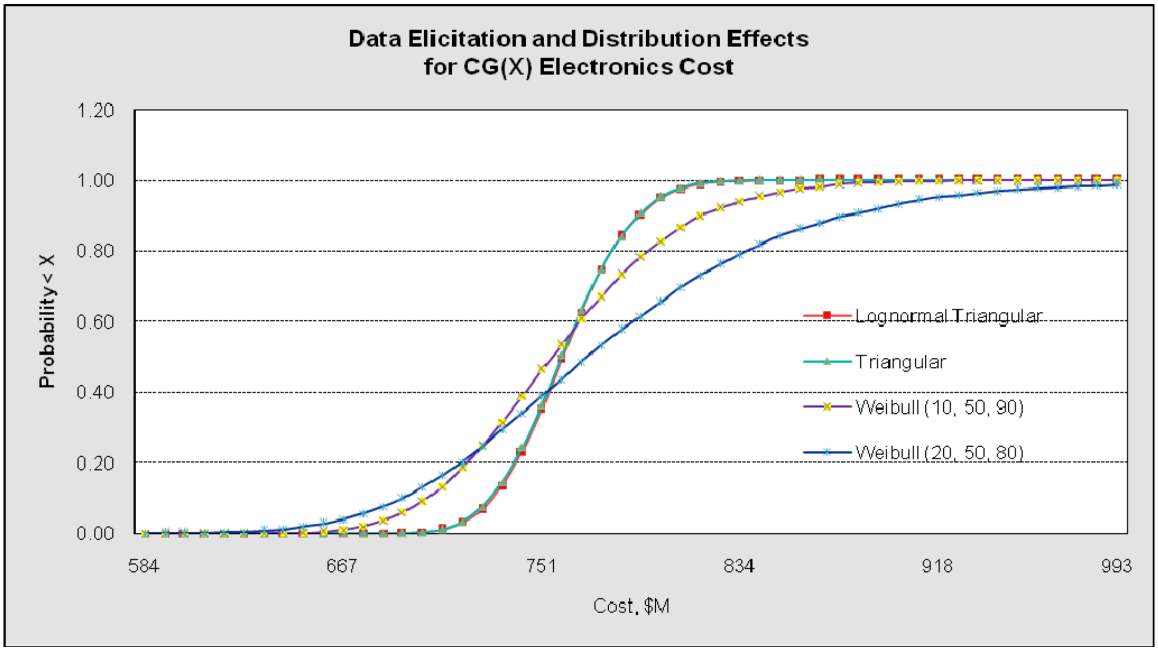


Figure 10. CG(X) Crystal Ball® Analysis, 10000 Runs showing the Effects of Distribution Choices on the cost Cumulative Distribution Functions.

The Weibull (10%, 50%, 90%) distribution shows a broader cost range for the given probability brackets. The tapering lower and upper bounds in comparison to the triangular and lognormal distribution represent a more likely cost outcome. The Weibull (20%, 50%, 80%) shows an even larger cost range, which makes sense because this distribution is supposed to model a more pessimistic view of cost. Both of these distributions are associated with higher costs as the probability of the cost increases. It is important to note the difference between the optimistic and pessimistic Weibull distributions in Figure 10. For each, the cost increases with an increase in probability, but it is clear that the model's results indicate that the cost risk is significantly higher using the pessimistic Weibull distribution.

3. Correlation Effects

Correlation effects are potentially important in modeling appropriate cost relationships between different elements of systems and are not conducted enough in current cost analysis models (Book, 2001). Trends with correlation tend to lean toward perfect correlation because of simplicity. Perfect correlation does help to widen the range

of outputs in the distribution functions, but this may not be an accurate or reliable representation. Reasonable correlation coefficients may provide more realistic and credible estimates of project costs, rather than assuming perfect or zero correlation. Assessing correlation coefficients is a difficult problem. A need exists for the investigation and development of a realistic and practical model to account for interrelationships between cost elements.

Two types of correlations are modeled in this thesis:

- Correlations among cost elements within the radar suite. The radar suite includes elements of X-band, S-band, Cooling, and Power. Dependencies among these components are mainly from subsystem characteristics such as complexity.
- Correlations among cost elements in the entire electronics suite. Dependencies among these cost elements occur from the programmatic and organizational considerations common to all cost elements that are a part of the same project (Kujawski et al., 2004).

There are two types of correlations: Pearson and Spearman. Pearson correlation coefficient determines the degree of linearity between two random variables, while Spearman rank order correlation coefficients measure monotonicity. Correlation among cost elements in the electronics suite is modeled with the use of the Correlation Matrix function in Crystal Ball®. Crystal Ball® uses rank correlations to correlate assumptions. This means that the values are not changed, but they are rearranged to produce the desired correlation. Rank correlation eliminates the need to explicitly model the dependence between the cost elements. Garvey (2000) advocates the use of Pearson's correlation. However, given the limited information, rank correlations offer the advantage of accounting for correlations independent of explicit distribution and dependency models. The use of Monte Carlo simulations generates the full PDF rather than simply expected value and variance.

This thesis uses three sets of two correlation coefficients to model the correlation between the radar suite elements and the rest of the electronics suite components. The first set models the distributions with correlation coefficients of 0.5 for the radar suite

elements and 0.5 for the entire electronics suite elements. The second set of correlation coefficients is 0.5 and 0.2. The third set uses correlation coefficients of 0.8 and 0.5. Figure 11 shows the correlation chart used for the (0.5, 0.2) correlation. The corresponding Weibull (20%, 50%, 80%) distribution model that the correlation chart in Figure 11 is applied to is shown in Figure 12.

To further explain the correlation chart in Figure 11, please consider the cell showing the correlation factor for the E7 (Weibull 20, 50, 80) and E8 (Weibull 20, 50, 80) cost elements. As indicated by Figure 12, the cells E7 and E8 correspond to the X-band and S-band systems, respectively. Both are components of the radar suite and therefore are likely to have strong dependencies. Weibull (20%, 50%, 80%) denotes that the elements are modeled using three-parameter Weibull distribution given by the 20th, 50th, and 80th percentiles. The correlation cell is determined by the intersection of the corresponding row and column for the two elements. The value of this cell is 0.50. This indicates that the correlation between the elements X-band and S-band of the radar suite are correlated by a factor of 0.5.

	E7 (Weibull 20, 50, 80)	E8 (Weibull 20, 50, 80)	E9 (Weibull 20, 50, 80)	E10 (Weibull 20, 50, 80)	E11 (Weibull 20, 50, 80)	E12 (Weibull 20, 50, 80)	E13 (Weibull 20, 50, 80)	E14 (Weibull 20, 50, 80)	E15 (Weibull 20, 50, 80)	E16 (Weibull 20, 50, 80)	E17 (Weibull 20, 50, 80)	E18 (Weibull 20, 50, 80)
E7 (Weibull 20, 50, 80)	1.000	0.500	0.500	0.500	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
E8 (Weibull 20, 50, 80)		1.000	0.500	0.500	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
E9 (Weibull 20, 50, 80)			1.000	0.500	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
E10 (Weibull 20, 50, 80)				1.000	0.200	0.200	0.200	0.200	0.200	0.200	0.200	0.200
E11 (Weibull 20, 50, 80)					1.000	0.200	0.200	0.200	0.200	0.200	0.200	0.200
E12 (Weibull 20, 50, 80)						1.000	0.200	0.200	0.200	0.200	0.200	0.200
E13 (Weibull 20, 50, 80)							1.000	0.200	0.200	0.200	0.200	0.200
E14 (Weibull 20, 50, 80)								1.000	0.200	0.200	0.200	0.200
E15 (Weibull 20, 50, 80)									1.000	0.200	0.200	0.200
E16 (Weibull 20, 50, 80)										1.000	0.200	0.200
E17 (Weibull 20, 50, 80)											1.000	0.200
E18 (Weibull 20, 50, 80)												1.000

Figure 11. CG(X) Crystal Ball® Analysis, 10000 Runs, Correlation (0.5, 0.2) chart for Weibull (20%, 50%, 80%) distribution model.

WBS	Low	Most Likely	High	Distribution Value	MAIMS 50%	MAIMS Mean	MAIMS 80%	Forecast
Electronics	**$ 633.57**	**$ 748.19**	**$ 910.20**	749.223	808.572	826.107	916.469	749.223
Radar Suite	**$ 190.32**	**$ 223.90**	**$ 257.49**	311.909	311.909	314.702	319.845	311.909
X-band	$ 62.30	$ 65.58	$ 75.41	74.152	74.152	74.152	75.431	74.152
S-band	$ 146.88	$ 154.61	$ 177.80	184.516	184.516	184.516	184.516	184.516
Cooling	$ 3.53	$ 3.71	$ 4.27	3.886	3.886	4.003	4.267	3.886
Power (included in Ship Total)	$ 46.17	$ 48.60	$ 55.89	49.355	49.355	52.031	55.632	49.355
ExComm	$ 100.72	$ 134.29	$ 188.01	99.392	132.510	147.348	187.390	99.392
TSCE	$ 56.49	$ 75.32	$ 94.15	67.366	75.895	75.946	94.676	67.366
IUSW	$ 25.09	$ 26.41	$ 27.73	26.075	26.421	26.429	27.755	26.075
EW-IW	$ 36.58	$ 48.78	$ 60.97	60.253	60.253	60.253	61.170	60.253
EO-IR	$ 11.69	$ 12.31	$ 12.92	11.946	12.312	12.314	12.927	11.946
IFF	$ 7.98	$ 8.40	$ 8.82	8.010	8.390	8.395	8.816	8.010
MS EI&T (SS Only)	$ 73.18	$ 91.47	$ 109.77	101.805	101.805	101.805	109.317	101.805
MS EI&T (CS Only)	$ 62.97	$ 78.71	$ 94.45	62.467	79.077	78.916	94.574	62.467

Figure 12. CG(X) Crystal Ball® Analysis, 10,000 Runs, Weibull (20%, 50%, 80%) distribution model with (0.5, 0.2) correlation.

Figure 13 is an overlay of the different probability distributions for the electronics suite cost, produced by using the following three different combinations of correlation coefficients for the radar suite and electronics suite:

- Correlation coefficients of 0.5 among the radar suite components and 0.2 between the different electronic suite components.
- Correlation coefficients of 0.5 among the radar suite components and 0.5 between the different electronic suite components.
- Correlation coefficients of 0.8 among the radar suite components and 0.5 between the different electronic suite components.

As discussed above, positive correlations give rise to broader distributions, which reflect higher uncertainty. The no correlation PDF in Figure 13 is the same as the no correlation shown in Figure 9. They do not appear to be the same due to the difference in scale and also due to the fact that they are from separate Monte Carlo simulations. Although the Monte Carlo simulations will give similar results for each run, they will not be identical. Analysis of the effects of the different correlation coefficients is discussed further in Section IV.C.

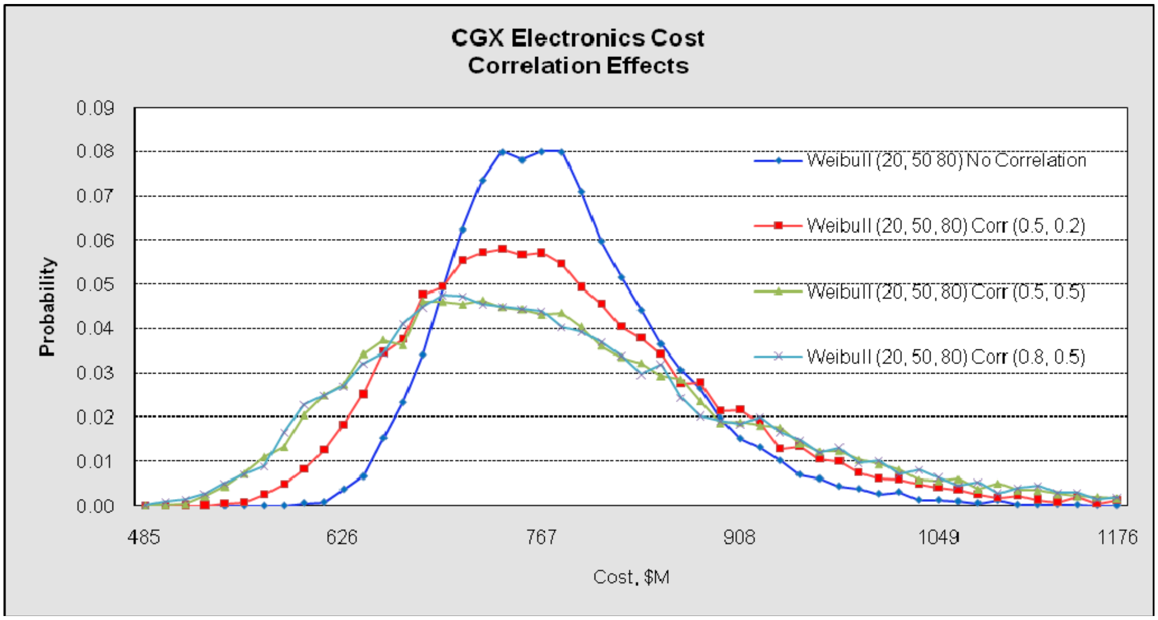


Figure 13. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite cost based on different correlation effects in cumulative probability form.

4. MAIMS Principle Effects

The MAIMS principle is modeled in this thesis by using the three-parameter Weibull (20%, 50%, 80%) distribution function and predetermined percentile points for the MAIMS set points. By implementing MAIMS into the distribution function, any value less than the money allocation point is equal to the money allocation value. The percentage parameters used for MAIMS are the 50th percentile or median, the mean, and the 80th percentile funding levels. A spike, or delta function, is observed in the MAIMS modified distributions at the money allocation points. These money allocation points correspond to the budget allocated to the WBS cost elements by the project manager.

The MAIMS modified functions are modeled by using the following equation:

If Distribution *Value < X, then X, else Distribution Value*

By using this equation, the value of the MAIMS modified distribution will never be less than the value X.

Figure 14 is a screenshot of a Monte Carlo simulation run with the MAIMS principle. The formula bar shows the equation used to simulate the MAIMS principle for cell G7. This equation was used for the three different MAIMS scenarios modeled.

Figure 15 shows the resulting PDFs obtained from the model in Figure 14. Further analysis of the effects of the MAIMS principle on cost is discussed more in depth later in this chapter, in Section IV.D.3.

G7 =+IF(E7<J7,J7,E7)

WBS	Low	Most Likely	High	Distribution Value	MAIMS 50%	MAIMS Mean	MAIMS 80%	Forecast	Mean
Electronics	$ 633.57	$ 748.19	$ 910.20	0	748.595	763.453	850.730	0	762.56
Radar Suite	$ 190.32	$ 223.90	$ 257.49	0	272.497	280.863	295.480	0	280.85
X-band	$ 62.30	$ 65.58	$ 75.41	0	65.539	67.532	70.946	0	67.53
S-band	$ 146.88	$ 154.61	$ 177.80	0	154.628	159.404	167.697	0	159.40
Cooling	$ 3.53	$ 3.71	$ 4.27	0	3.718	3.825	4.020	0	3.82
Power (included in Ship Total)	$ 46.17	$ 48.60	$ 55.89	0	48.612	50.102	52.817	0	50.10
ExComm	$ 100.72	$ 134.29	$ 188.01	0	135.110	141.225	169.453	0	141.23
TSCE	$ 56.49	$ 75.32	$ 94.15	0	75.241	75.297	87.679	0	75.30
IUSW	$ 25.09	$ 26.41	$ 27.73	0	26.420	26.416	27.289	0	26.42
EW-IW	$ 36.58	$ 48.78	$ 60.97	0	48.502	48.708	56.774	0	48.71
EO-IR	$ 11.69	$ 12.31	$ 12.92	0	12.304	12.303	12.704	0	12.30
IFF	$ 7.98	$ 8.40	$ 8.82	0	8.402	8.403	8.678	0	8.40
MS EI&T (SS Only)	$ 73.18	$ 91.47	$ 109.77	0	91.472	91.545	103.568	0	91.54
MS EI&T (CS Only)	$ 62.97	$ 78.71	$ 94.45	0	78.646	78.693	89.105	0	78.69

Figure 14. CG(X) Crystal Ball® Analysis, 10000 Runs, Electronics Suite costs including the MAIMS principle.

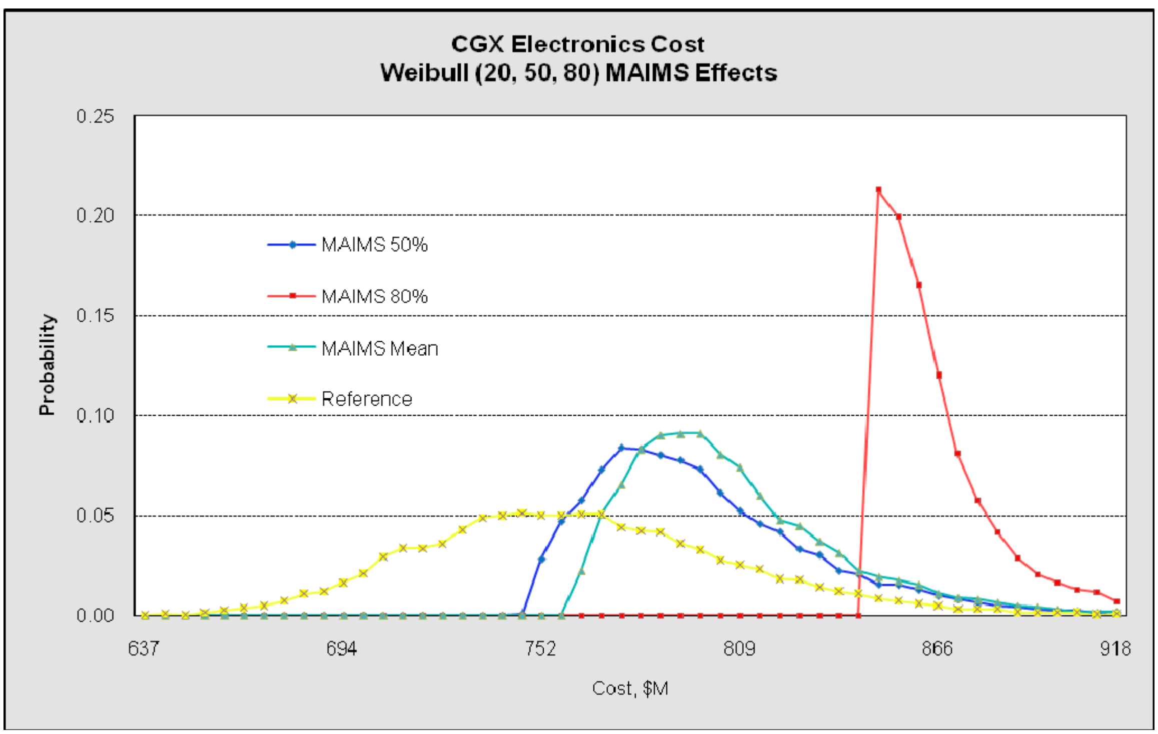


Figure 15. CG(X) Crystal Ball® Analysis, 10000 Runs, Electronics Suite costs including the MAIMS principle, PDFs.

5. Other Factors

Uncertainty ranges for the low, most likely, and high values are modeled using triangular distribution functions and a Monte Carlo simulation. The purpose of doing this simulation is to ensure that any uncertainty effects from the low, most likely, and high values could be accounted for in the model. By doing this, the low, most likely, and high values become assumption cells as defined by Crystal Ball®. These assumptions are used for the input parameters of the "Distribution Value" cell, which gives the cost value of the particular element. The results indicate that the total cost distribution has values essentially indistinguishable from the original. This is because sampling the distributions of the individual low, most likely, and high values produces values that are very similar to using the original values. Because the modeling did not significantly change the result of the input parameters to the "Distribution Cell," uncertainty distribution functions for the low, most likely, and high values were not used in the model for this thesis. Figure 16 shows the model used for this experiment.

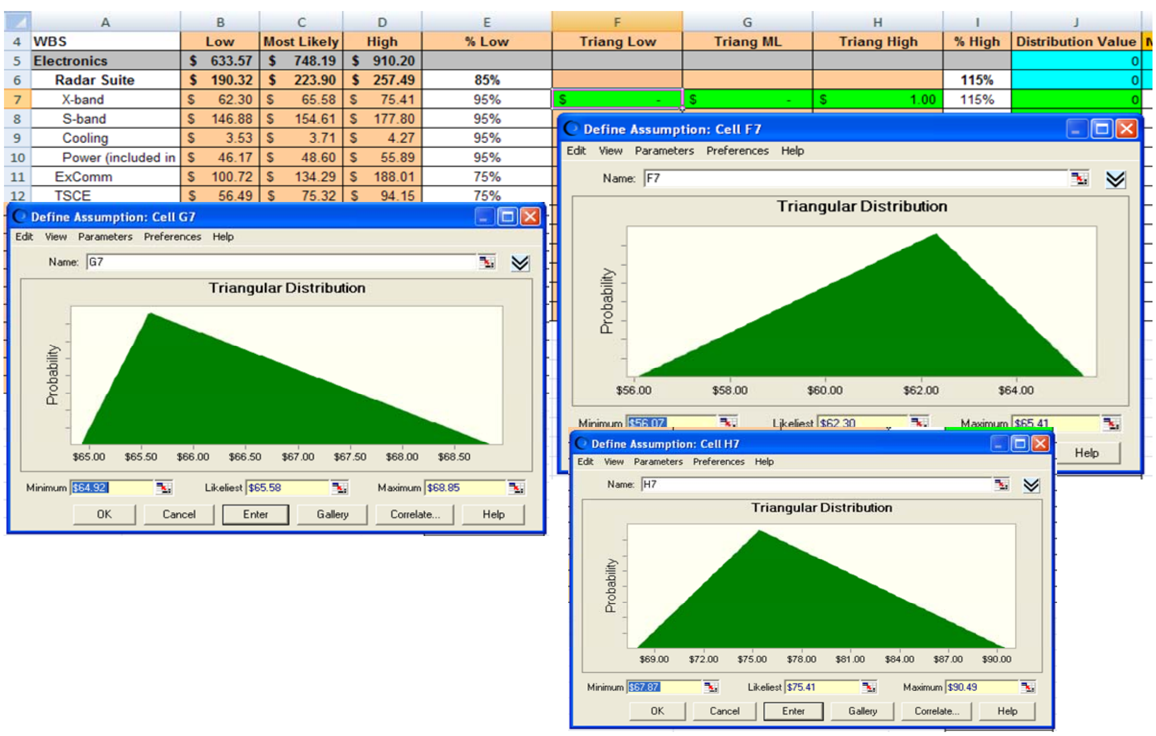


Figure 16. CG(X) Crystal Ball® Analysis, 10000 Runs, Modeling Low, Most Likely, and High values: Low Value Distribution.

C. DESCRIPTION OF THE CRYSTAL BALL MODEL

This section describes the modeling and analysis of the cost factors discussed in Section IV.B using Crystal Ball®.

The model for the CG(X) cost analysis for this thesis is developed by using the template provided by NAVSEA 05C for their CG(X) cost model. Specifically, it utilizes the low, most likely, and high cost values for the triangular distribution from the Mission Systems Risk Assessment worksheet. The low, high, and 50th percentile values are used as the input parameters for the three-parameter Weibull probability distributions, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%). The lognormal distributions used the means and standard deviations of the corresponding triangular distributions. These cost element distributions were created and simulations were run with Crystal Ball® software. Figure 17 is a screenshot of a single step run of a Monte Carlo simulation for a given set of PDFs.

WBS	Low	Most Likely	High	Distribution Value	MAIMS 50%	MAIMS Mean	MAIMS 80%	Forecast
Electronics	$ 633.57	$ 748.19	$ 910.20	743.6651596	775.150	771.210	816.878	743.6652
Radar Suite	$ 190.32	$ 223.90	$ 257.49	280.4829027	281.845	282.157	292.309	280.4829
X-band	$ 62.30	$ 65.58	$ 75.41	67.9865584	67.987	67.987	70.391	67.98656
S-band	$ 146.88	$ 154.61	$ 177.80	160.0935981	160.094	160.094	165.789	160.0936
Cooling	$ 3.53	$ 3.71	$ 4.27	3.765910723	3.817	3.839	3.984	3.765911
Power (included in Ship Total)	$ 46.17	$ 48.60	$ 55.89	48.63683552	49.949	50.238	52.146	48.63684
ExComm	$ 100.72	$ 134.29	$ 188.01	145.9576333	145.958	145.958	157.587	145.9576
TSCE	$ 56.49	$ 75.32	$ 94.15	58.71313762	75.332	75.291	82.153	58.71314
IUSW	$ 25.09	$ 26.41	$ 27.73	27.54032701	27.540	27.540	27.540	27.54033
EW-IW	$ 36.58	$ 48.78	$ 60.97	49.18924453	49.189	49.189	53.234	49.18924
EO-IR	$ 11.69	$ 12.31	$ 12.92	11.94642499	12.307	12.305	12.525	11.94642
IFF	$ 7.98	$ 8.40	$ 8.82	8.312572255	8.395	8.396	8.554	8.312572
MS EI&T (SS Only)	$ 73.18	$ 91.47	$ 109.77	82.91683278	82.917	91.606	84.592	82.91683
MS EI&T (CS Only)	$ 62.97	$ 78.71	$ 94.45	78.60608439	91.667	78.767	98.383	78.60608

Figure 17. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of CG(X) single step Monte Carlo Simulation.

The left column of the model shows the components of the electronics suite. The next three columns contain the data that was acquired from the NAVSEA 05C Excel® worksheets. The "Distribution Value" column contains green boxes, which correspond to the assumptions for the cost elements. The assumption cells are defined as probability

distributions and contain the random variables for the cost elements. The blue boxes in the "Distribution Value" column are the forecasts that refer the sum of the assumption boxes as follows: (1) The radar suite cost is the probabilistic sum of the X-band radar, S-band radar, cooling, and power costs; and (2) the electronics cost is the probabilistic sum of the cost of the radar suite, the ExComm, TCSE, IUSW, EW-IW, EO-IR, IFF, and MS EI&T costs. The MAIMS columns represent the values for the simulation that correspond to a MAIMS modified distribution. The MAIMS 50% column represents a distribution truncated at the 50th percentile, while the MAIMS mean is truncated at the mean value, and the MAIMS 80% is the distribution modified to start at the 80th percentile value of the baseline distributions.

Figure 18 shows a snapshot of how the distribution parameters are input into the model for a triangular distribution. The low, most likely, and high cost values are entered in the appropriate blocks in the dialog screen called "Define Assumption" to develop the distribution that will be represented by the appropriate cell. In this case, the cell being defined is E7.

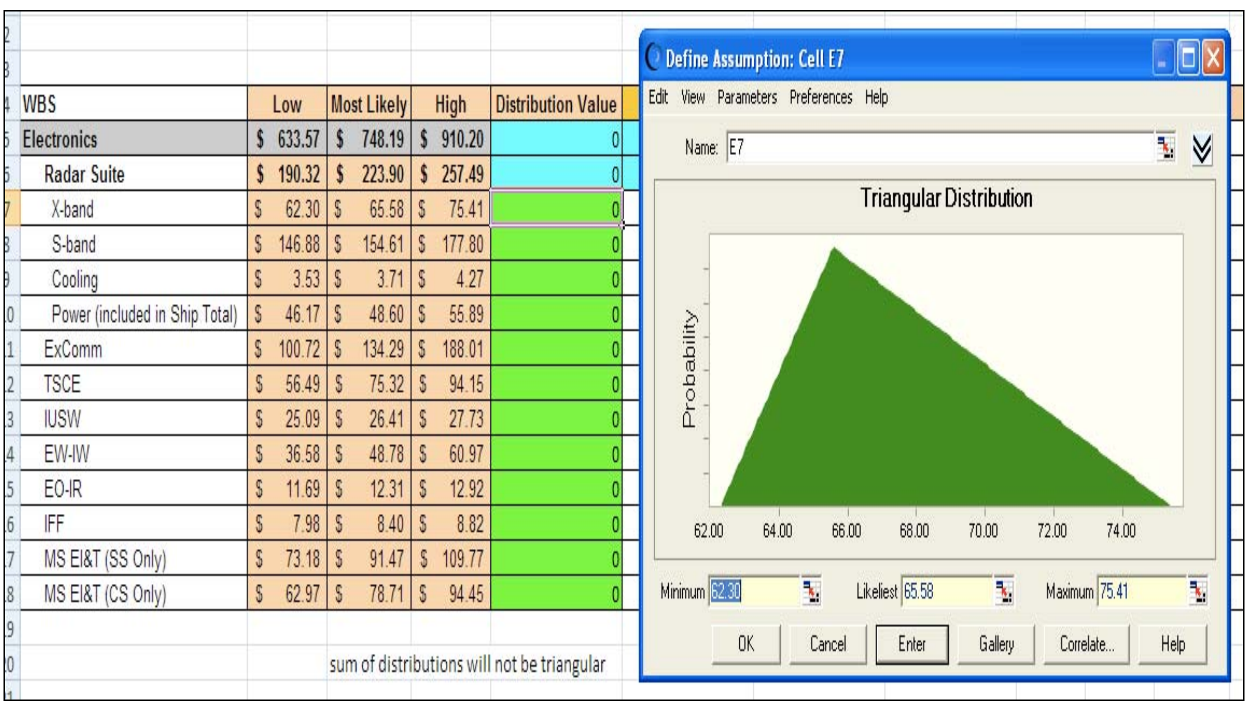


Figure 18. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of the Development of Triangular Distribution Function.

Figures 19, 20, and 21 are screenshots of how distributions are created for the lognormal, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%) distributions. For Figure 18, the lognormal distribution, and the input parameters of mean and standard deviation are obtained from the results of the triangular distribution function from Figure 17. The three-parameter Weibull distributions shown in Figures 19 and 20 use the low values as either the 10th or 20th percentiles and the high values as the 80th or 90th percentiles, depending on the function and the 50th percentile for the third parameter. Note that for Figures 20 and 21, the distributions represented for cell E7 (X-band) is highly skewed. This is due to the fact that the low and most likely values are very similar, while the high values are significantly higher, skewing the resulting distribution.

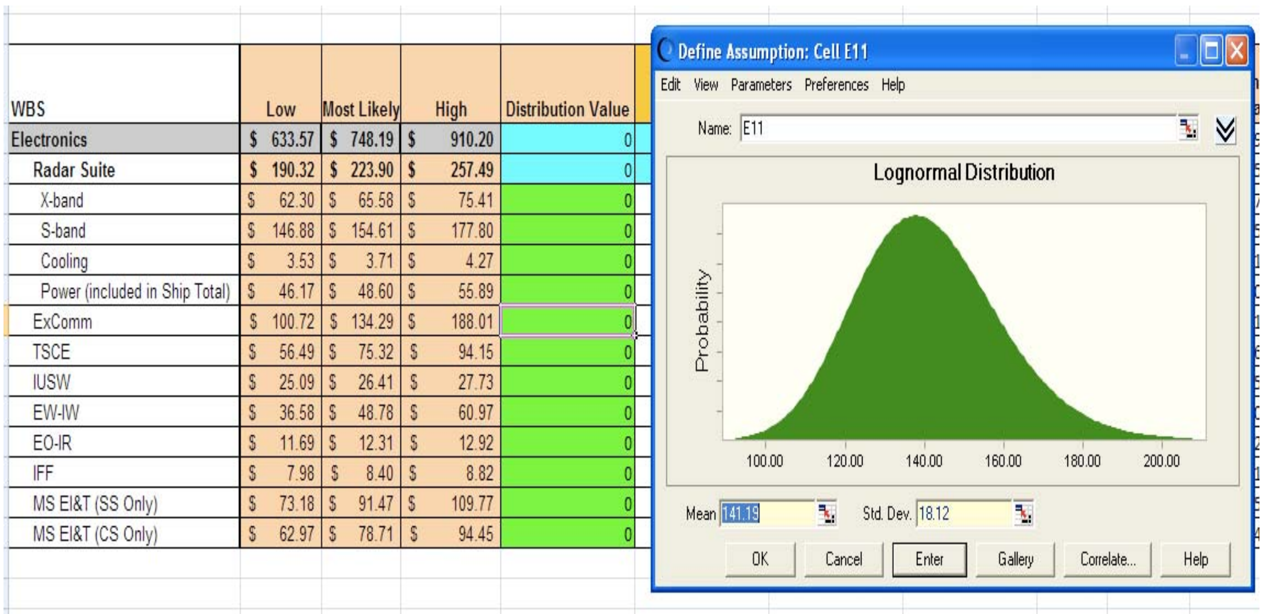
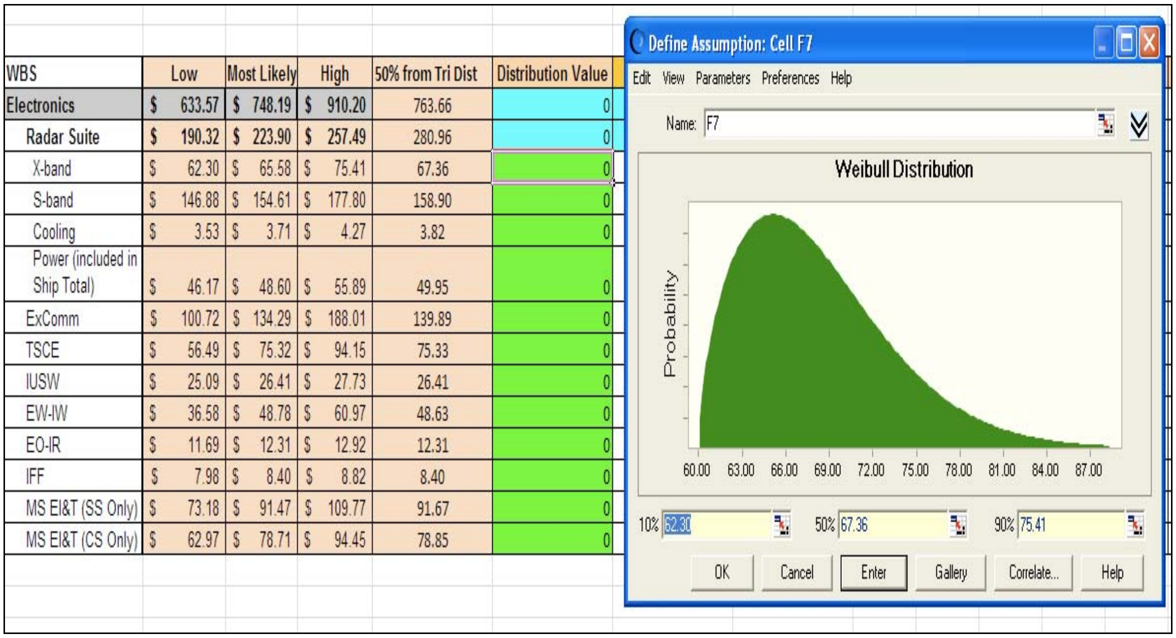
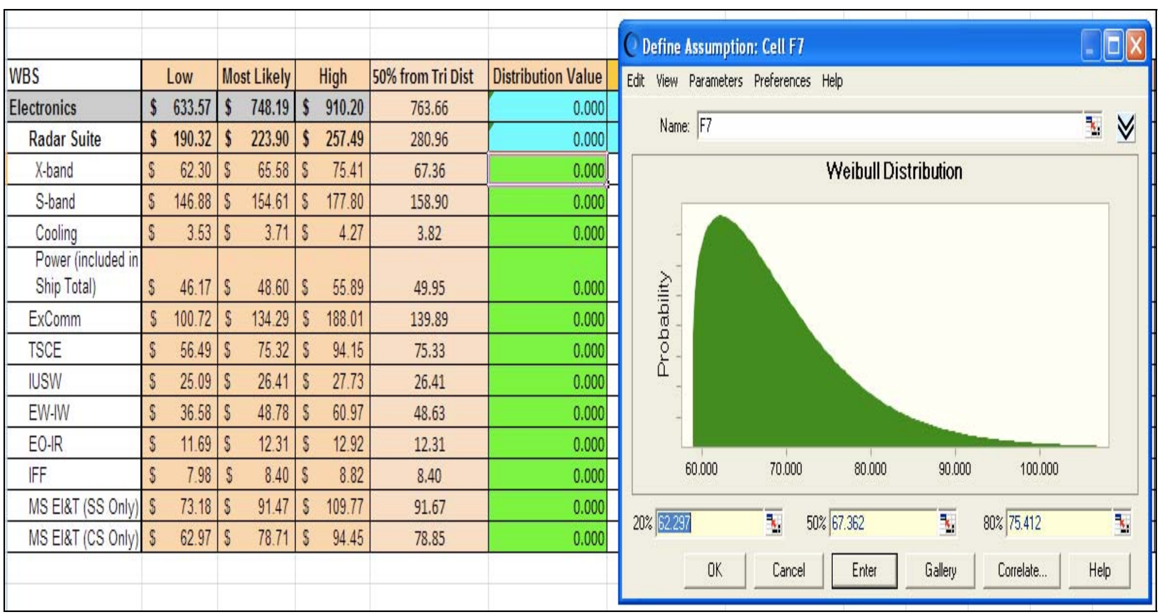


Figure 19. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of the Development of Lognormal Distribution Function.



WBS	Low	Most Likely	High	50% from Tri Dist	Distribution Value
Electronics	$ 633.57	$ 748.19	$ 910.20	763.66	0
Radar Suite	$ 190.32	$ 223.90	$ 257.49	280.96	0
X-band	$ 62.30	$ 65.58	$ 75.41	67.36	0
S-band	$ 146.88	$ 154.61	$ 177.80	158.90	0
Cooling	$ 3.53	$ 3.71	$ 4.27	3.82	0
Power (included in Ship Total)	$ 46.17	$ 48.60	$ 55.89	49.95	0
ExComm	$ 100.72	$ 134.29	$ 188.01	139.89	0
TSCE	$ 56.49	$ 75.32	$ 94.15	75.33	0
IUSW	$ 25.09	$ 26.41	$ 27.73	26.41	0
EW-IW	$ 36.58	$ 48.78	$ 60.97	48.63	0
EO-IR	$ 11.69	$ 12.31	$ 12.92	12.31	0
IFF	$ 7.98	$ 8.40	$ 8.82	8.40	0
MS EI&T (SS Only)	$ 73.18	$ 91.47	$ 109.77	91.67	0
MS EI&T (CS Only)	$ 62.97	$ 78.71	$ 94.45	78.85	0

Figure 20. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of the Development of Weibull (10%, 50%, 90%) Distribution Function.



WBS	Low	Most Likely	High	50% from Tri Dist	Distribution Value
Electronics	$ 633.57	$ 748.19	$ 910.20	763.66	0.000
Radar Suite	$ 190.32	$ 223.90	$ 257.49	280.96	0.000
X-band	$ 62.30	$ 65.58	$ 75.41	67.36	0.000
S-band	$ 146.88	$ 154.61	$ 177.80	158.90	0.000
Cooling	$ 3.53	$ 3.71	$ 4.27	3.82	0.000
Power (included in Ship Total)	$ 46.17	$ 48.60	$ 55.89	49.95	0.000
ExComm	$ 100.72	$ 134.29	$ 188.01	139.89	0.000
TSCE	$ 56.49	$ 75.32	$ 94.15	75.33	0.000
IUSW	$ 25.09	$ 26.41	$ 27.73	26.41	0.000
EW-IW	$ 36.58	$ 48.78	$ 60.97	48.63	0.000
EO-IR	$ 11.69	$ 12.31	$ 12.92	12.31	0.000
IFF	$ 7.98	$ 8.40	$ 8.82	8.40	0.000
MS EI&T (SS Only)	$ 73.18	$ 91.47	$ 109.77	91.67	0.000
MS EI&T (CS Only)	$ 62.97	$ 78.71	$ 94.45	78.85	0.000

Figure 21. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of Development of Weibull (20%, 50%, 80%) Distribution Function.

Correlation distributions are created by using the Correlation Matrix function of Crystal Ball®. Specific correlation coefficients are entered into the distribution functions

of assumption cells in the dialog window under the “Correlate” button. When the model is run with correlation coefficients set for specific distribution functions, the results are now correlated. Figure 22 is a screenshot showing how correlation coefficients are added to an assumption cell.

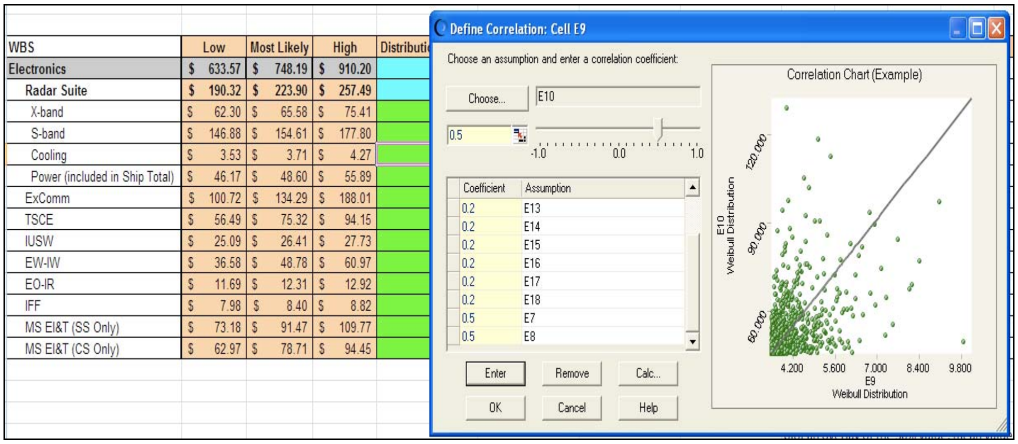


Figure 22. CG(X) Crystal Ball® Analysis, 10000 Runs, Screenshot of Development of Model using Correlation Coefficients.

After the models are developed and run 10000 times, overlays are created to graphically show the results. These overlays are described in more detail in Section IV.D.

D. RESULTS

1. Effects of Distribution Choice on Cost Forecast

The first distributions modeled were the single electronics suite elements with different distributions. For the purpose of this thesis, the element ExComm is chosen for this explanation. Figure 23 shows the cumulative frequency distribution of the different modeled distributions for the ExComm element. The triangular and lognormal distributions show similar characteristics, which is expected since the lognormal distribution uses parameters taken from the triangular distribution (mean and standard deviations). Both Weibull distributions show expected characteristics. The Weibull (20%, 50%, 80%) definitely indicates a more pessimistic cost forecast because as the cumulative probability increases, the cost increases more significantly than for the

Weibull (10%, 50%, 90%) distribution. This overlay indicates that the choice of distribution used in modeling does play a significant part in results obtained for cost. The three-parameter Weibull distributions represent a more realistic cost outcome for high risk components. Weibull distributions allow for modeling of highly complex distributions using DFA, while triangular distributions have a more restrictive shape, making it difficult to fit three arbitrary percentiles for the low, most likely, and high values (Kujawski et al., 2004).

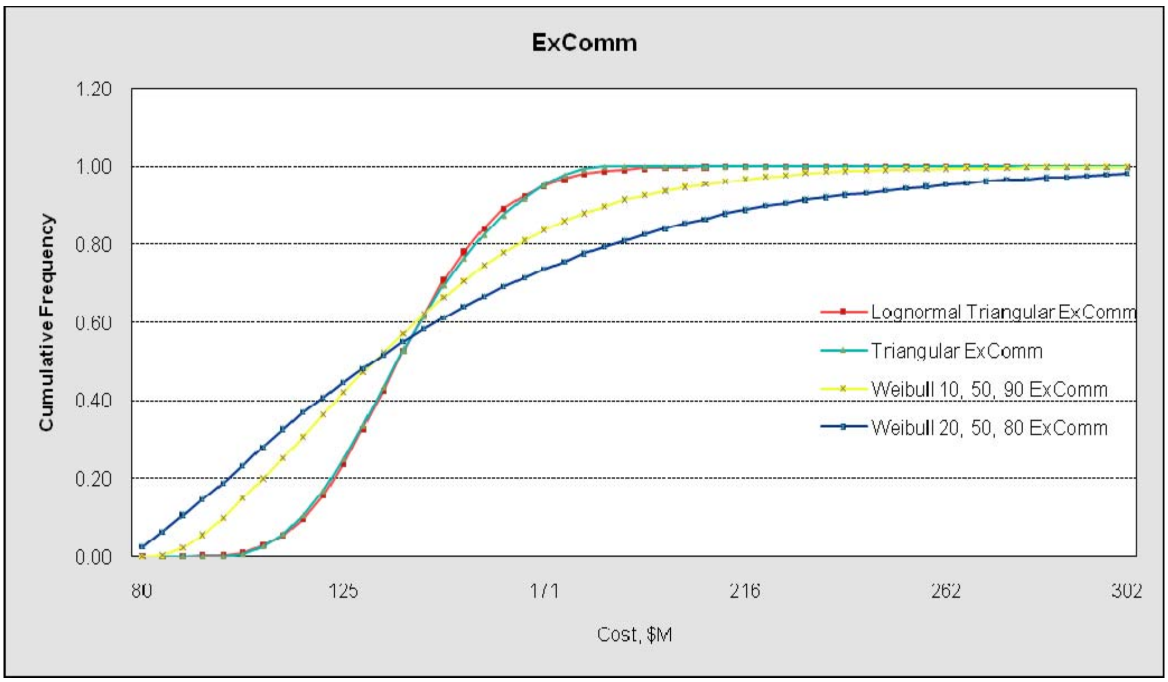


Figure 23. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite element ExComm cumulative frequency distributions for different probability distributions.

The probability distribution functions shown in the overlay in Figure 24 illustrate expected behaviors for the ExComm PDFs. Both the triangular and lognormal distributions are narrow because the triangular distribution upper and lower bounds do not allow for infinite upper cost ranges. The sum of the Weibull (20%, 50%, 80%) distributions shows a more pessimistic behavior in comparison to the sum of the Weibull (10%, 50%, 90%) distributions.

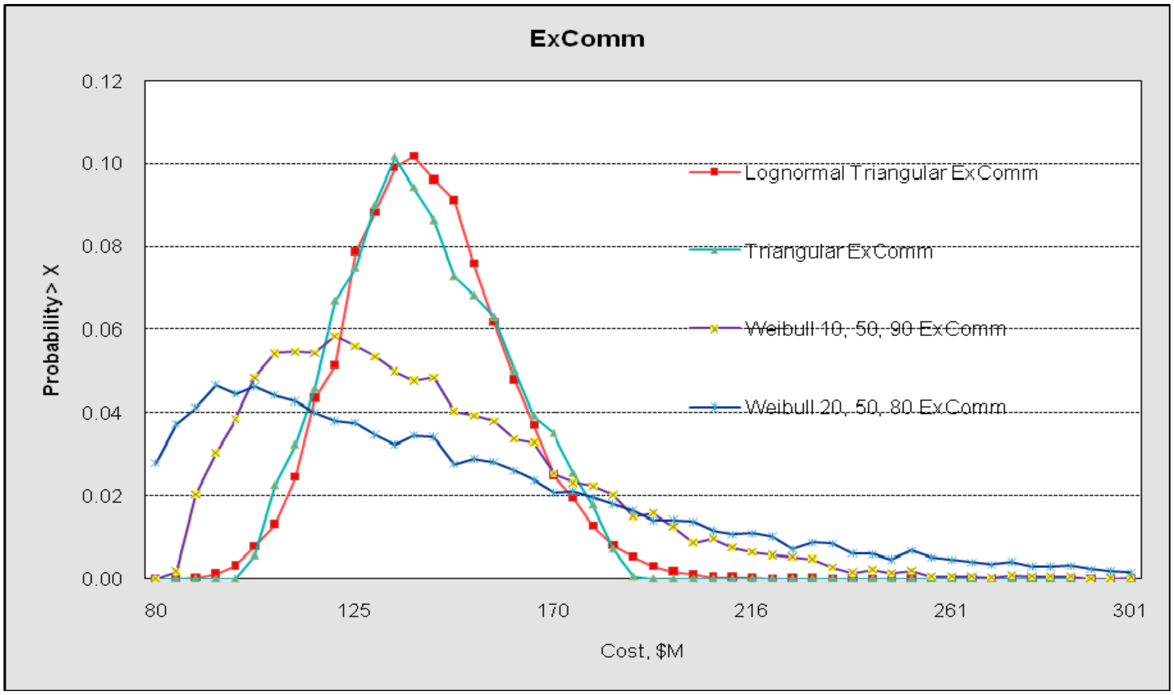


Figure 24. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite element ExComm with different PDFs.

Once all the individual electronics suite elements are modeled, they are summed up probabilistically in the main worksheet in Excel to obtain the entire electronics suite cost. The simulation selects a random value from each of the element distributions then adds them to create one data point for the total cost. This is repeated 10000 times to create the total cost distribution. When all the distribution functions (assumption cells in the model) of the electronics suite elements are probabilistically summed, the resulting cost is illustrated in the overlay shown in Figure 25. All four distributions have the appearance of a normal distribution consistent with the Central Limit Theorem (Garvey, 2000).

The lognormal and triangular distribution functions give rise to relatively narrow total cost distributions, consistent with the finite ranges of the contributing triangular distributions and the modeling of the lognormal distributions using the corresponding mean and standard deviation values. The Weibull (10%, 50%, 90%)-based cost distribution shows narrower behavior for cost range than the Weibull (20%, 50%, 80%)-based distribution. The Weibull (20%, 50%, 80%)-based distribution allows for more uncertainty in data elicitation from SMEs. Weibull distributions not only show higher

probabilities of cost overruns, but also higher probabilities of cost underruns. These underruns reflect the assumption of 10% and 20% as the low value parameter for the distribution, rather than using it as the minimum value. Figure 26 shows the same data as Figure 25, except that it is in the cumulative probability form.

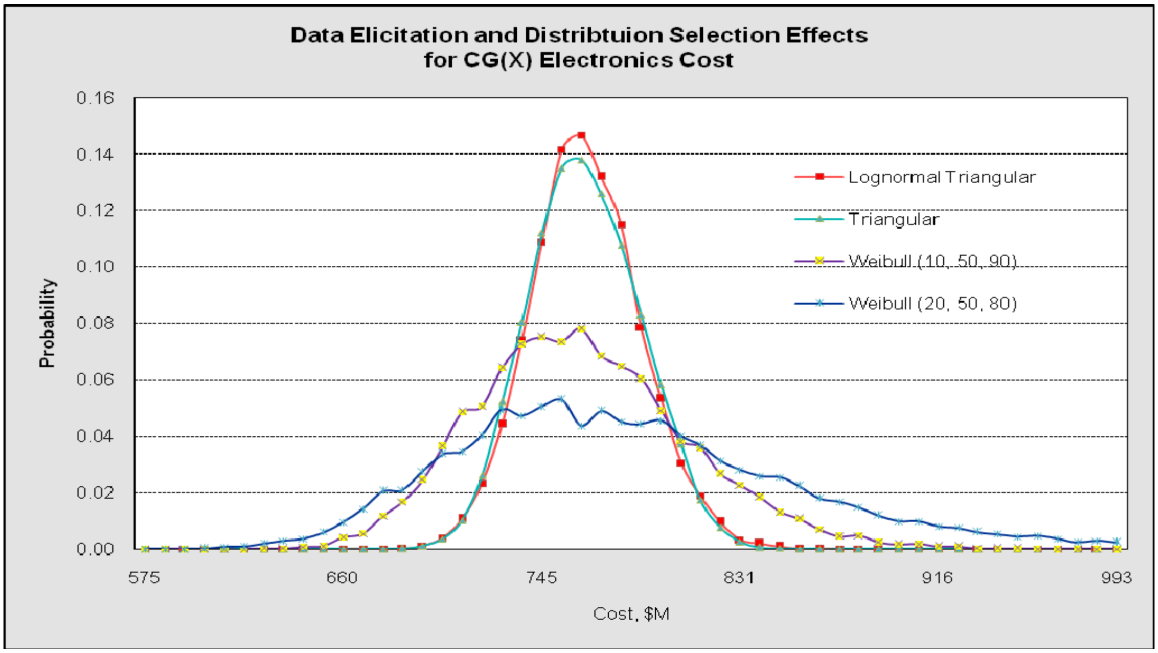


Figure 25. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite Cost based on different distribution selections.

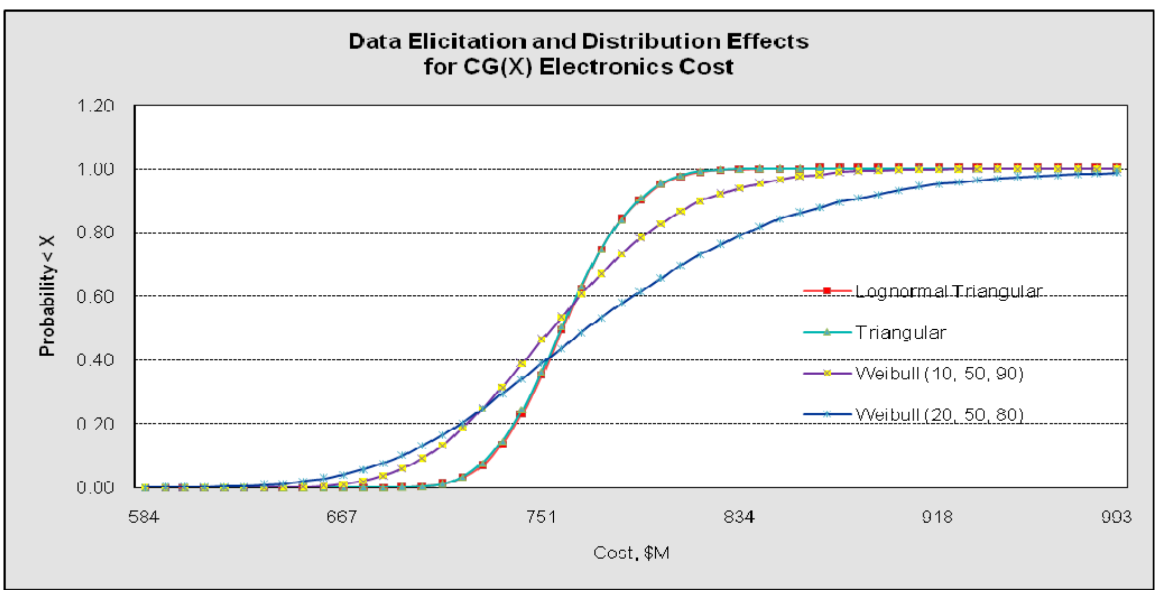


Figure 26. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite cost based on different distribution selections in cumulative probability form.

2. Effects of Correlation on Cost

As discussed in Section IV.B.1, two types of correlations are modeled in this thesis: (1) Correlations among cost elements within the radar suite, and (2) correlations among cost elements in the entire electronics suite. This thesis uses the following three different correlation coefficient factors to show the correlation between the radar suite elements and the rest of the electronics suite components:

- Radar suite correlation coefficient = 0.5, electronics suite correlation coefficient = 0.5
- Radar suite correlation coefficient = 0.5, electronics suite correlation coefficient = 0.2
- Radar suite correlation coefficient = 0.8, electronics suite correlation coefficient = 0.5.

The choice to use the values listed above is to simulate an environment that is not a perfectly correlated or no-correlation situation. The (0.5, 0.5) correlation assumes that there is an equal correlation relationship between the subcomponents of the radar suite and the elements of the electronics suite. The (0.5, 0.2) correlation illustrates the effects of having a stronger correlation between the elements of the electronics suite than between elements of the entire electronics suite. The (0.8, 0.5) correlation show the impact of a stronger correlation between components of one system than between different systems. These correlation coefficients represent a limited set of parameters for investigation in this thesis. Further research in the determination of appropriate correlation coefficients and their effect is needed to provide a more complete analysis.

The impact of correlation effects is seen in Figures 27 and 28. These overlays show the different distributions that are a result of a 10000-run Monte Carlo simulation for the correlated distributions in cumulative distribution form (Figure 27) and PDF form (Figure 28). The blue PDF is the reference Weibull (20%, 50%, 80%) distribution with no correlation effects. This distribution has the narrowest cost range when compared with the correlated distributions. The cost ranges of the Weibull distribution increases as the correlation factors increase. Also, in the cumulative probability distribution shown in Figure 27, all of the distributions intersect at the mean value for the cost.

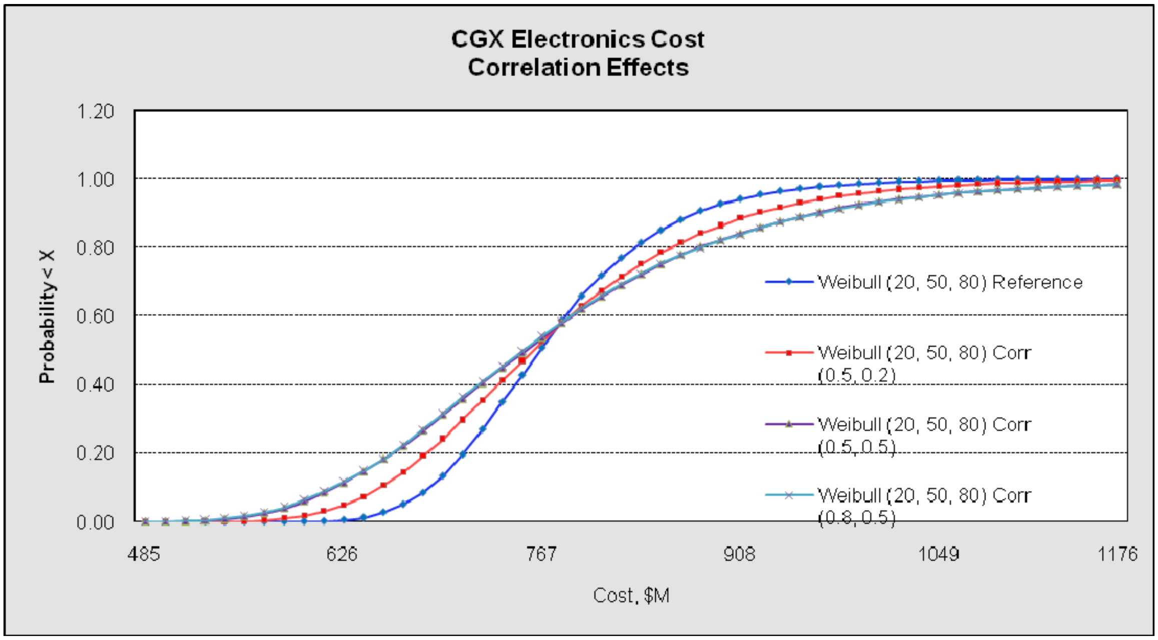


Figure 27. Figure 27: CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite Cost showing the impact of different correlation effects.

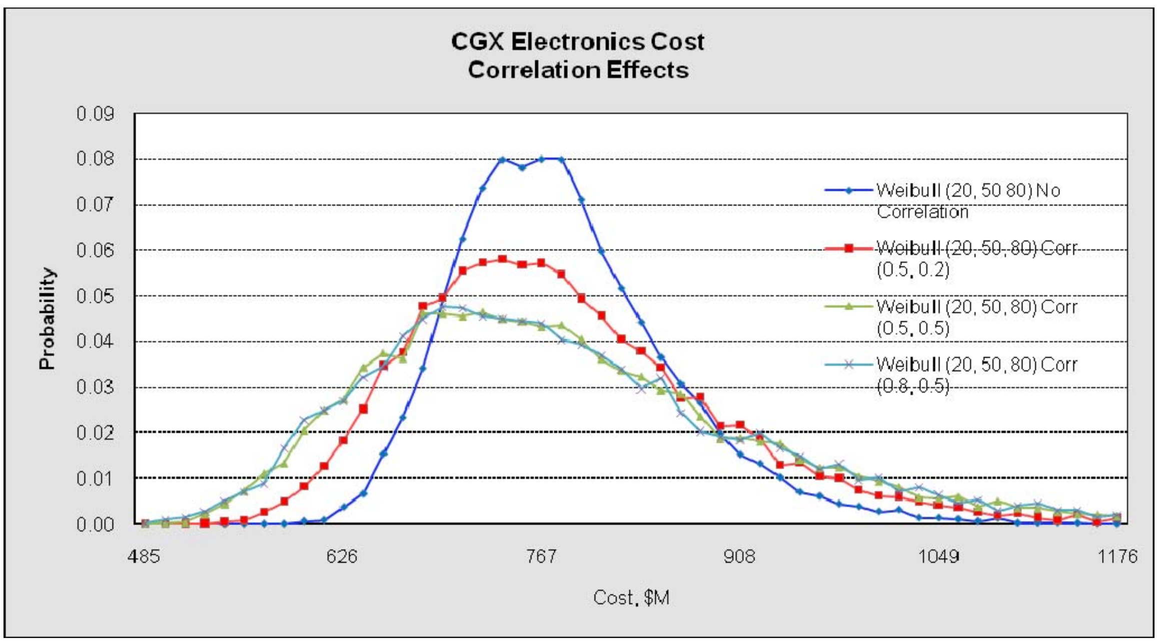


Figure 28. Figure 28: CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite cost based on different correlation effects in cumulative probability form.

As expected, the (0.5, 0.2) correlation being the smallest has the least effect on the total cost distribution. It is interesting to note that the distribution resulting from the

(0.5, 0.5) correlation does not differ much from the (0.8, 0.5) distribution, but that both of these correlations have a more significant effect than the (0.5, 0.2) correlation. This indicates that a change in the the correlation factor for the radar suite from 0.5 to 0.8 is not as significant as a change in the correlation factor from 0.2 to 0.5 for the different components of the entire electronics suite. These results suggest that the correlation effects are important for probability values midpoint between the mean and the extremes, but there is little difference for values beyond 0.5. The results in Figure 28 are consistent with theoretical predictions of positive correlation effects in that the total cost becomes broader than for uncorrelated total cost (Kujawski et al., 2004). Further investigations are recommended to quantify correlation effects.

3. MAIMS Effects on Cost

The MAIMS modified cumulative probability and density density distributions for the electronics suite cost are shown in Figures 29 and 30. Characteristics of the MAIMS modified PDF is that they will never have a value less than the chosen value of modification. So, for the MAIMS 50th percentile modified distribution in Figure 29, the distribution has no value less than the 50th percentile baseline cost level. In Figure 30, the spikes or delta functions normally associated with the individual MAIMS distributions are not seen as they are modulated when summed.

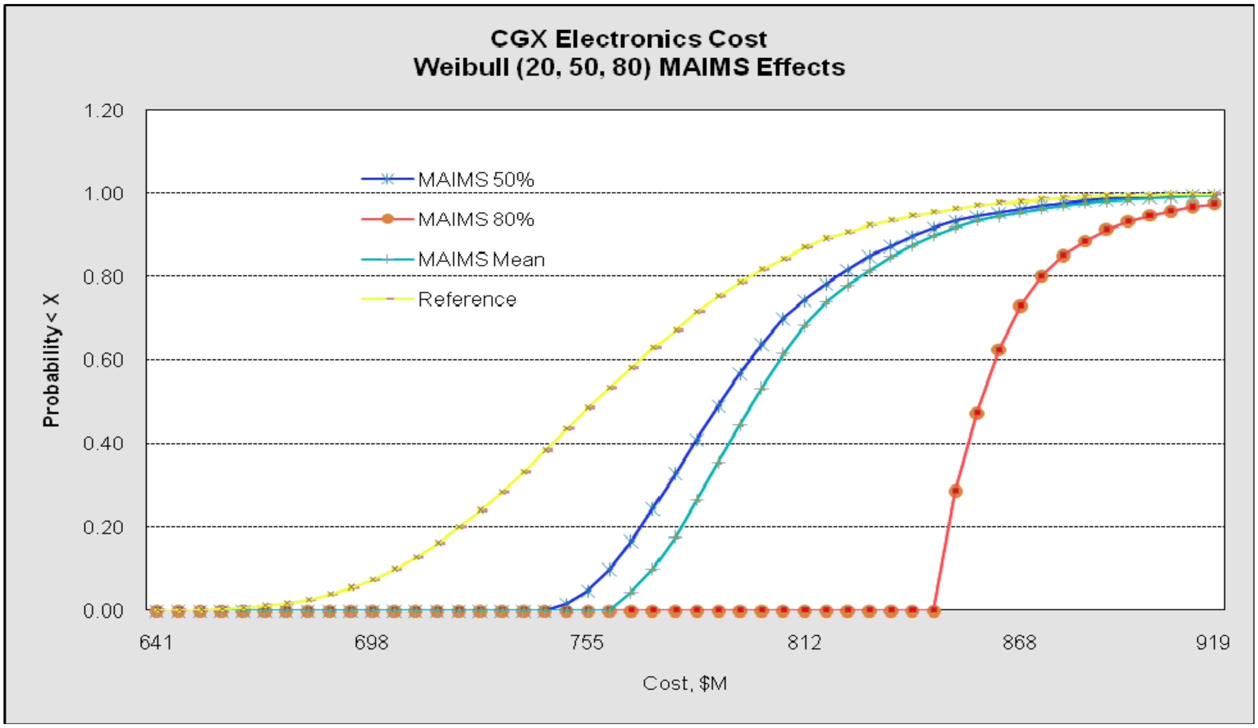


Figure 29. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite cost showing the MAIMS effects in cumulative probability form.

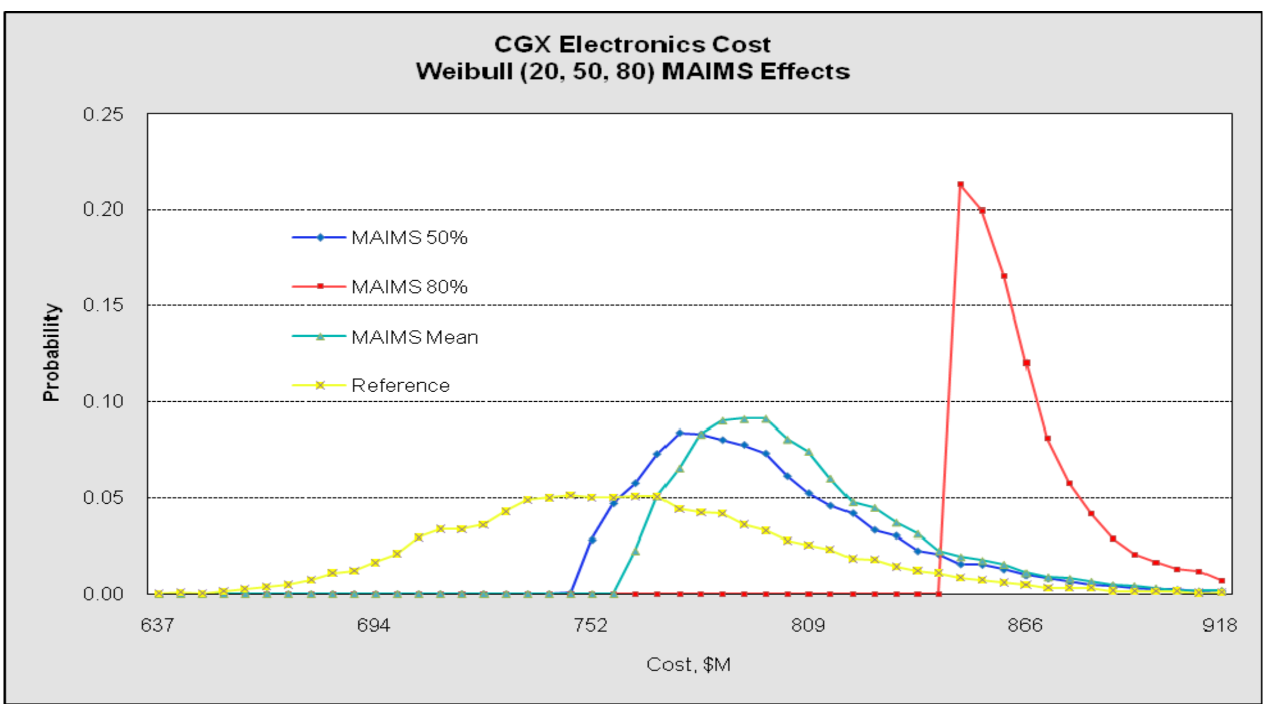


Figure 30. CG(X) Crystal Ball® Analysis, 10000 Runs, Overlay of Electronics Suite cost showing the MAIMS effects in PDF form.

It is important to note the significant rise in cost curve that occurs as the MAIMS modification value increases. The mean value of the distribtion increases as the funding level increases, and this is very clear in Figure 29. The curve representing the MAIMS 80% distribution shows how the budget is always high when comparing it to the MAIMS 50% or MAIMS mean distribution. This effect is because once money has been allocated to a WBS element, it is almost never seen in cost savings as underruns, because cost account managers never return money to the project. Any remaining money from one WBS is subsequently spent on a different existing WBS that has cost overruns.

These simulations can be considered with other cost factors in making program management decisions regarding budgets. Funding projects at a level too low to cover costs will lead to cost overruns, while funding at a level that is too high leads to money not being recouped as savings later. Allocating reasonable budgets is the goal.

E. CHAPTER SUMMARY

The research for this thesis is based on the NAVSEA 05C CG(X) model provided by Mr. Chris Deegan and his CG(X) analysts. The CG(X) model encompasses all factors considered for cost of the entire program, including labor rates, material cost, overhead cost, planning cost, and other factors. Because of the complexity of the model and the numerous factors to consider, one portion of the model was chosen for analysis. The Electronic Suite and its nine elements are specifically targeted as the focus for analysis.

The steps used in the analysis of the CG(X) model are:

1. Analyze the cost factors used by NAVSEA 05C to develop the electronics cost.
2. Analyze the PDFs used for the electronics cost elements.
3. Identify what data elicitation methods were employed.
4. Determine if correlation factors were used in the cost analysis.
5. Develop cost factors to be modeled in a new model.
6. Decide which PDFs to use in the new model.
7. Develop a new cost model using correlation factors, chosen PDFs, and MAIMS influenced distributions.

Identified cost factors include NAVSEA 05C's probability distribution choice, method used for developing the low, most likely, and high cost values for the electronics suite elements, data elicitation methods, and correlation effects. This thesis explores the methodology in choosing different probability distribution functions and their applicability to the model. Specifically, triangular, lognormal, and two variations of the three-parameter Weibull distribution are considered.

Methods of data elicitation are explored and the use of a DFA method is recommended for future use, although the research in this thesis did not involve data acquisition. To simulate the use of a DFA methodology, Weibull distributions are employed to account for uncertainty associated with SME estimation of data. A Weibull (10%, 50%, 90%) distribution is used to simulate a more optimistic view of the uncertainty of data, while a Weibull (20%, 50%, 80%) distribution models a more pessimistic, but probably more realistic, view of the uncertainty associated with data from the SMEs.

Two types of correlation effects are considered and modeled in this thesis. The first is the correlation between subcomponents of the radar suite and the other is the correlation between the elements of the electronics suite. The radar suite is one of the elements that make up the electronics suite. Analysis shows that a more significant effect is experienced with higher correlation between the elements of the electronics suite than between the subcomponents of the radar suite.

MAIMS modified probability distributions are modeled to show the significance of budget allocation level. These distributions are truncated at the baseline budget with a delta function at the baseline. This is based on the principle that once a budget is allocated, money is almost never seen in the form of cost under runs as the project progresses. As the MAIMS modification value increases, overall distribution cost rises with increasing probability of success.

THIS PAGE INTENTIONALLY LEFT BLANK

V. CONCLUSIONS

A. SUMMARY

This thesis begins by exploring the definitions of risk and how it applies to the guidance set forth by current Navy leadership. Admiral Gary Roughead, Chief of Naval Operations, states that, “We manage risk” (Roughead, 2007). The need to develop effective acquisition and shipbuilding methods to successfully deliver an “affordable future fleet” (McCoy, 2008) is imperative if the Navy is to meet the goal of a 313-ship Navy by 2020. Cost risk analysis is one tool of many that can be used to help attain this goal.

This thesis then proceeds to examine the probabilistic cost analysis approach that NAVSEA 05C currently uses to predict new naval vessel construction costs and to develop a method that better predicts the ultimate cost risk. Cost factors analyzed in this thesis include the effect of data elicitation, distribution choice, the impact of the MAIMS principle, and the effect of correlation factors. Data elicitation and MAIMS have significant impact. Correlation effects vanish at the minimum, mean, and maximum values. PDF selection has a small impact as long as the distributions fit the three specified percentiles.

The model provided by NAVSEA 05C encompasses all aspects of the ship’s cost and only the nine elements of the electronics suite were chosen for analysis in this thesis. Using data obtained from SMEs for low, most likely, and high cost values, experiments were conducted for the noted cost factors in the Excel® Monte Carlo simulation add-in Crystal Ball®.

Triangular, lognormal, Weibull (10%, 50%, 90%) and Weibull (20%, 50%, 80%) distributions are modeled and simulated to show the impact that each distribution can have on budget considerations for program managers. Both the triangular and lognormal distributions show narrow cost ranges when compared to the Weibull distribution cost range. The Weibull (10%, 50%, 90%) represents a more optimistic distribution than the more pessimistic Weibull (20%, 50%, 80%) distribution. The Weibull (20%, 50%, 80%)

distribution accounts for the optimism bias commonly associated with SMEs. Data elicitation effects are modeled through the use of the Weibull distributions.

Correlation among cost elements in the electronics suite is modeled with the use of the Correlation Matrix function in Crystal Ball®. This thesis uses three sets of two correlation coefficients to model the correlation between the radar suite elements and the rest of the electronics suite components. The results suggest that the correlation effects are important for probability values midpoint between the mean and the extremes, but there is little difference for values beyond 0.5. Further investigations are recommended to quantify correlation effects.

MAIMS principle modified distributions are modeled with the 50th percentile cost value, mean, and 80th percentile cost value to show the impact of funding at these different levels. The MAIMS principle is based the observation that for a given budget, any money allocated is considered money spent. Very rarely are cost underruns experienced on a project once the budget has been allocated. The MAIMS modified distributions in this thesis show the impact of either under-funding a budget or over-funding. Under-funding leads to cost overruns and over-funding leads to an overall higher cost, since money allocated is unlikely to be recouped.

B. RECOMMENDATIONS AND AREAS FOR FURTHER RESEARCH

The analysis conducted in this model is only a starting point for improvements in the area of cost analysis for naval vessels. Although the methodology used in this thesis provides a framework for obtaining more accurate predictions of cost than those in use with current probabilistic cost analysis, more work is required to develop a more complete and tested model. Recommendations for future research in the area of probabilistic cost analysis for shipbuilding include:

- Use of the DFA method to obtain data for cost assessment. Recommend eliciting data from SMEs at the 10th, 50th, and 90th percentiles, at a minimum, for relatively optimistic view of the data quality, and at the 20th, 50th, and 80th percentiles if a more pessimistic view of the quality of data is present. Take into consideration the overconfidence of estimates

provided by experts in their field and use this knowledge when calibrating data for analysis.

- Select flexible and realistic probability distribution functions for cost analysis. Create probability distribution functions from historical data and adjust for expected differences in new programs.
- Incorporate the use of correlation among cost elements of a system. Aim to use a range of correlation coefficients that is realistic. A reasonable range for correlation coefficients is between 0.3-0.6, with some room for variation. Overly optimistic correlation coefficients that assume independence and overly pessimistic correlation coefficients that assume perfect correlation rarely exist in real data.
- Use the "Money Allocated is Money Spent" (MAIMS) principle to model budget management behavior. The MAIMS function will not allow the system cost to be a lesser amount than the budgeted cost baseline.
- Investigate further capabilities available with advanced modeling software such as Crystal Ball® or @Risk.
- Incorporate systems engineering methodologies and thinking into the development of probabilistic cost analysis. Kujawski et al. (2004) state that this is the single greatest challenge to the development and use of improved cost models.

Continuing with the development of improved cost models is an important step in helping the Navy to ensure the successful acquisition of the 313-ship Navy it desires. Improved cost models can give project managers the ability to develop more realistic and successful plans for their projects, while enabling them to make better budget decisions. The cost analysis methodology presented in this thesis can serve as a starting point for further advanced research in this area that can be used by different programs across the Navy.

THIS PAGE INTENTIONALLY LEFT BLANK

LIST OF REFERENCES

Alpert, M., & Raiffa, H. (1982). A progress report on the training of probability assessors, Judgment under uncertainty: Heuristics and biases. D. Kahneman, P. Slovic, & A. Tversky (Eds.), Cambridge: Cambridge University Press, 294-305.

Augustine, N.R. (1997). Augustine's laws: A top executive looks at the complexities and conundrums of today's business management – and offers solutions. The American Institute of Aeronautics and Astronautics, Inc.

Bernstein, P.L. (1998). Against the gods: The remarkable story of risk. John Wiley and Sons, Inc.

Book, S. (2001). Systems Engineering: Estimating probable system cost. *Crosslink*, (*2*)1.

Cavas, C. (2008a, July 24). DDG 1000 program will end at 2 ships. Retrieved on September 3, 2008 from http://www.navytimes.com/news/2008/07/defense_ddg1000_072208.

Cavas, C. (2008b, May 29). Why no one believes the navy. Retrieved on September 3, 2008 from http://www.defensenews.com/story.php?i=3548400.

Deegan, C. (2007a, December). Cost engineering at the naval sea systems command. Presentation at Naval Postgraduate School, Monterey, CA.

Deegan, C. (2007b, December). When is cost growth actually cost realism: Understanding 700 years of cost growth. Presentation at Naval Postgraduate School, Monterey, CA.

Deegan, C., & Fields, M. (2007, December). SCN cost risk analysis. Presentation at Naval Postgraduate School, Monterey, CA.

Defense Acquisition Acronyms and Terms, Eleventh Edition. (2003, September). Defense Acquisition University Press.

Department of the Navy, Report to Congress on Annual Long-Range Plan for Construction of Naval Vessels for FY2007 (February 2006).

Fields, M., & Popp, M. (2007, October 11). Risk – Lessons Learned. Presentation at *Navy Cost Analysis Symposium*.

Garvey, P.R. (2000). Probability methods for cost uncertainty analysis. Marcel Dekker, Inc.

Government Accountability Office. (2007, July 2). *GAO cost assessment guide*.

Graves, R. (2001, December). Open and closed: The Monte Carlo model. PM Network, 48-53.

Keeney, R.L., & von Winterfeld, D. (1991). Eliciting probabilities from experts in complex technical problems. IEEE Trans Engineering Management, *39*(3), 191-201.

Kujawski, E., & Angelis, D. (2007, July 5). Research proposal – FY2008: Acquisition research program: Dynamic cost risk assessment for controlling the cost of naval vessels.

Kujawski, E., Alvaro, M., & Edwards, W. (2004). Incorporating psychological influences in probabilistic cost analysis. *Systems Engineering*, *7*(3), 195-216.

Littoral Combat Ship Program. (2008, September). Retrieved on August 23, 2008 from http://www.globalsecurity.org/military/systems/ship/lcs-program.htm.

McCarthy, J.F. (2008, April 18). Navy approach to risk-based decision making. Presentation at Naval Postgraduate School, Monterey, CA.

McCoy, K.M. (2008, August 8). The first 100 days: Executing NAVSEA'S strategic business plan.

Moran, S.R. (1999, January). Cost-risk analysis – The devil is in the details, space. Los Angeles: Systems Cost Analysis Group.

NAVSEA. (2005). *Cost Estimating Handbook*. Retrieved on August 25, 2008 from http://www.ncca.navy.mil/resources/2005_NAVSEA_CEH_Final.pdf.

Navy of the Future: CG(X). Retrieved on August 15, 2008 from http://www.navy.com/about/shipsequipment/navyofthefuture.

O'Rourke, R. (2008, June 10). CRS report for Congress: Navy force structure and shipbuilding plans: Background and issues for Congress.

PMBOK Guide. (2004). A guide to the project management body of knowledge (3rd ed.). Project Management Institute.

Portny, S., Mantel, S., Meredity, J., Shafer, S., & Sutton, M. (2008). Project management: Planning, scheduling, and controlling projects. John Wiley and Sons.

Roughead, G. (2007, October 25). Chief of Naval Operations, CNO Guidance for 2007-2008.

Scully, M. (2007, May). Winter, Mullen statements foretell of dramatic changes in shipbuilding, sea power.

Spear, R. (1939, July 10). Letter from Secretary of the Navy to the Chief of the Bureau of Supplies and Accounts: Cost of Naval Vessels.

Wittwer, J.W. (2004, June 1). Monte Carlo simulation basics from Vertex42.com. Retrieved on August 30, 2008 from http://vertex42.com/ExcelArticles/mc/MonteCarloSimulation.html.

THIS PAGE INTENTIONALLY LEFT BLANK

INITIAL DISTRIBUTION LIST

1. Defense Technical Information Center
   Ft. Belvoir, VA

2. Dudley Knox Library
   Naval Postgraduate School
   Monterey, CA

3. ATTN: RADM Terry Benedict, PEO IWS
   Commander, Integrated Warfare Systems
   Washington Navy Yard, D.C.

4. ATTN: Mr. Chris Deegan
   Integrated Warfare Systems
   Washington Navy Yard, D.C.

5. ATTN: Mrs. Jill Boward, NAVSEA 05C
   Commander, Naval Sea Systems Command Cost Engineering and Industrial Analysis
   Washington Navy Yard, D.C.

6. ATTN: Mr. Morris Fields, NAVSEA 05C
   Commander, Naval Sea Systems Command Cost Engineering and Industrial Analysis
   Washington Navy Yard, D.C.

7. ATTN: Dr. Edouard Kujawski
   Naval Postgraduate School
   Monterey, CA

8. ATTN: Mr. Jeff Kline
   Naval Postgraduate School
   Monterey, CA

9. ATTN: Dr. Diana Angelis
   Naval Postgraduate School
   Monterey, CA

10. ATTN: Dr. Daniel Nussbaum
    Naval Postgraduate School
    Monterey, CA